Which Job Skills Are Complementary to IT Adoption and Use?*

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Abstract: Previous research has shown that the returns to computer use vary by occupation and the types of software applications used. We use data on nine different job skill requirements from the BLS' National Compensation Survey to examine which skills may be important in explaining the wage premium attributable to IT adoption and use in North America. The data on job skills are linked to individuals in recent U.S. Current Population Survey's Computer and Internet Use Supplements and the 1999–2004 Canadian Workplace and Employee Survey (WES), by detailed occupation and major industry. Using the panel in the WES and employing a first-differences model, we are able to control for time-invariant individual and establishment-level unobserved heterogeneity. For both countries, we find that workers whose jobs are more autonomous and involve interactive tasks receive a wage increase from using a desktop computer in general. Furthermore, we find that people skills are complementary to e-mail use, word processing, and management applications. The ability to work autonomously is complementary to e-mail use and word processing. We also find that using computer-aided technologies, such as industrial robots, are complementary to performing physically-demanding tasks.

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I. Introduction

A seminal paper by Krueger (1993) using the U.S. Current Population Survey Computer Use Supplement (CPS) established a strong positive correlation between computer use and wages. He also showed that this correlation varied by the type of software application used. Krueger's findings have been widely debated in the literature, most notably by DiNardo and Pischke (1997), who demonstrated a similar correlation between wages and using a pencil on the job in Germany, and who argued that the observed computer wage premium was due to selection effects. Since then, researchers from around the world (Entorf and Kramarz 1997; Entorf, Gollac, and Kramarz 1999; Haisken-DeNew and Schmidt 1999; Arabsheibani et al. 2004; Dolton and Makepeace 2004; Pabilonia and Zoghi 2005; Di Pietro 2007; Kuku et al. 2007; Zoghi and Pabilonia 2007; Spitz-Oener 2008) employing various panel data and IV techniques to control for unobserved individual, and sometimes establishment, heterogeneity have found a small return (less than 4%) or no return to computer use *per se* for the average worker, depending on the time frame, sample used, and identifying variables. However, researchers using some of these same techniques have also shown that returns to computer use vary considerably by occupation and by the types of computer applications used (Di Pietro 2007; Zoghi and Pabilonia 2007).

Returns to computer use may vary for numerous reasons, including which skills these computers will complement or how long it takes to learn a particular computer skill. It may be easier to learn a specific computer application for individuals with higher learning ability. Returns to experienced users and new users may also be different because of differences in skill levels between adopters over time, as suggested in the literature on computer diffusion (e.g. Borghans and ter Weel 2004). However, until recently, it has been unclear whether workers are rewarded for their computer skills or for using computer-complementary skills on the job. Levy and Murnane (1996) found that in the 80's and 90's computers reduced the time spent on the routine tasks (data transfer, data entry, and computations) and increased the time spent on more difficult tasks (data rework, valuation, communication, and analysis) performed by accountants in the custodian unit of the Tammany bank. Autor, Levy, and Murnane (2003) used U.S. data from the Dictionary of Occupational Titles (DOT) to examine how tasks associated with occupations have changed over time. They showed that computers are substitutes for routine tasks and complements to analytical and interactive non-routine cognitive tasks. Using German employee data on self-reported skills over several decades, Spitz-Oener (2006) showed that most of the changes in skill requirements over time resulted from changes in task measures within occupation rather than in the occupational structure of employment. She also found that computerization within occupations results in increases in analytical and interactive task requirements. Using a British Skills Survey with information on self-reported job requirements, Green et al. (2007) found that computing skills have recently become more complementary to an index of "Influence Skill", which they derived from survey items that captured "the importance of: persuading or influencing others; instructing, training, or teaching people; making speeches or presentations; writing long reports; analyzing complex problems in depth; and planning the activities of others." Using a cross-section of individuals from Germany in the 1990s, Spitz-Oener (2008) provided some evidence that employees who perform computer-complementary tasks, specifically analytical and interactive tasks, earn a wage premium for computer use because computers increase their marginal product. She also showed that individuals in more recent years did not earn a similar premium for using pencils.

There have also been several papers examining whether there is a return to different computer skills using indicators for software applications instead of computer hardware

(Dickerson and Green 2004; Green et al. 2007; Zoghi and Pabilonia 2007; Dolton and Pelkonen 2008). We retest whether there is a return to using different software applications *per se* or whether these applications boost the wages only of individuals whose job requires a special skill set. For example, some researchers (Krueger 1993; Lee and Kim 2004; Dolton, Makepeace, and Robinson 2007; Di Pietro 2007; Dolton and Pelkonen 2008) have found a return to e-mail/internet use using cross-sectional data. However, Zoghi and Pabilonia (2007) did not find that workers earned a return in the short-run to using a computer when the main applications used were communication technologies, such as e-mail and internet. Recently, there has also been growing interest in measuring the effects of interpersonal skills on wage growth (Borghans, ter Weel, and Weinberg 2008). Communications software may be complementary to certain interpersonal skills. We provide estimates for the effect of using a computer for communication applications and show that differences in the level of interactive tasks required across occupations can explain some of the previously found return to e-mail applications.

The innovation in this paper is that we allow the returns to a variety of IT uses to vary by detailed information on required job skills from a large representative survey of U.S. establishments. Thus, we uncover which job skills are associated with these differential returns by occupation, as long as workers are matched to jobs based upon these skill requirements. We do so using two different recent data sets containing information on computer and IT use – the U.S. Current Population Survey's Computer and Internet Supplement (henceforth referred to as the CPS Supplement) and the Canadian Workplace and Employee Survey (WES). An advantage of using the Canadian data over the CPS Supplement is that it contains a panel so we can also control for individual time-invariant unobserved heterogeneity, such as the ability to adapt quickly to technological change. We can also control for establishment-level differences in pay.

We examine how returns to job skills vary for new computer adopters as well as users with varying years of computer experience.

II. Data and Descriptives

We use several data sets in our analyses. We obtain data on job skills by occupation and industry from the BLS National Compensation Survey (NCS). These job skills are linked to employees in the CPS Supplement and the WES using detailed occupation and major industry codes.

A. Job Skills in the NCS

The NCS is an ongoing restricted–use dataset collected by the Bureau of Labor Statistics[1]. The NCS was created to adjust federal pay rates to be comparable to those in the private sector. Unlike the DOT and its antecedent O*NET whose coverage of U.S. occupations is not universal, the NCS is representative of the non-agricultural, non-Federal sectors of the U.S. economy.[2] The data were first collected in 1997 by field economists who visited about 19,800 sampled establishments and randomly selected 5–20 workers from the establishment's personnel records for a total sample of 137,191 workers, covering about 477 occupations in 1997 and 475 occupations in 2003. In this paper, we will use NCS data collected through 2004, although in this draft we currently only use data from 1997 and 2002–2004. Detailed information about the

[1] For a detailed description of the NCS, see Pierce (1999).

[2] One disadvantage of using all of these data sets is potential measurement error due to miscoding of occupations. Comparing occupations in the CPS to those in the Occupational Employment Statistics (OES), Abraham and Spletzer (2009) found that the CPS underreported low-skilled jobs. In this case, we would expect our estimates of the returns to skills that we would expect to be highly compensated to be biased towards zero.

jobs of these workers, but no demographic information about the workers themselves, was obtained through interviews with human resources representatives from each establishment. The unique feature of the dataset that we explore is a group of "generic leveling factors", which are intended to measure required job skills consistently across occupations. The survey was not designed to measure the qualifications of the worker, but the actual job requirements, which are likely to be related to workers' skills to the extent that employers recruit workers to match worker skills with job duties (Pierce 1999).

These leveling factors include: knowledge; supervision received; guidelines; complexity; scope and effect; personal contacts; purpose of contacts; physical demands; work environment.[3] All factors were originally recorded on Likert scales, ranging from 1–3 to 1–9.[4] We assign the skill factors to each individual based on the skill factors for that occupation as reported in the NCS. Because different establishments report different ratings for each factor, we calculated the median of each factor for each three-digit 1990 Census occupation code by major SIC code cell. We then match the occupation and industry cells to those used in the WES and to those used in the CPS, so that workers observed in WES/CPS can be assigned a corresponding median skill level according to their job.[5] To maintain respondent privacy, we are only able to create a median for those occupation/industry cells that represent at least seven job observations. This decreases our sample size by about 11 percent for the WES. We lose approximately 5 percent of the 1997 CPS sample and 9 percent of the 2003 CPS sample when considering this same set of

[3] In 1997, the NCS also asked about supervisory duties. BLS staff have referred to this factor as experimental and it was subsequently dropped from the survey. Thus, we do not include it in our main specifications. From 2005 forward, the NCS only recorded 4 generic leveling factors.
[4] A Likert scale is ordinal. Therefore, we can only determine whether a wage would be higher or lower with a higher or lower score on the scale and not the percentage change in the wage given a point increase in the score.
[5] A detailed crosswalk between Census occupations and industry codes and WES codes, which are based upon Canadian 1979 SOC, is available upon request from the authors.

linked jobs skills.[6] Below we provide a brief summary of what each factor measures and how it could relate to technology use.

Leveling Factors (scale in parentheses)

1. Knowledge (1-9): measures the nature and extent of information or facts which the workers must understand and skills needed to apply that knowledge. A score of one indicates that the job requires only knowledge of simple, routine tasks with little or no previous training or experience. A score of nine indicates sufficient mastery of a professional field to develop new theories and hypotheses. In addition, a higher score should be associated with the ability to perform cognitive, non-routine tasks, which are not easily programmable and have previously been found to complement computer use (Autor, Levy, and Murnane 2003; Spitz-Oener 2008).
2. Supervision received (1-5): measures the nature and extent of direct or indirect controls exercised by the supervisor, the control exercised by the employee, and the degree of review of completed work. A score of one indicates that the employee follows precise, detailed instructions, and consults with the supervisor on all matters not covered by these instructions. A score of five indicates that the employee works independently, subject to broad missions given by the supervisor. We expect that those workers whose jobs are more autonomous (i.e. high score) to be more likely to use a computer to complement their work.
3. Guidelines (1-5): measures the nature of guidelines (such as handbooks, desk manuals, established procedure guides and reference materials) and the judgment

[6] Using the CPS, we are able to perform our analyses without this restriction; however, results are substantially the same.

needed to apply them. A score of one indicates that the employee works in strict adherence to specific, detailed guidelines, covering all important aspects of the work. A score of five indicates that the employee uses personal judgment in applying the intent of broad, non-specific guides. A low score would be associated with doing more routine work for which a computer may be a substitute while a high score would be associated with the employee performing more non-routine or complex, cognitive tasks, which have previously been found complementary to computer use (Autor, Levy, and Murnane 2003; Spitz-Oener 2008).

4. Complexity (1-6): measures the nature, number, variety, and intricacy of tasks or steps in the work. A score of one indicates a few clear-cut, closely related tasks, and the work is thus quickly mastered. A score of six indicates work that requires broad, intense effort and that involves several phases being pursued concurrently or sequentially. This skill is likely a complement to IT use since a high score indicates non-routine work.
5. Scope and effect (1-6): measures the relationship between the nature of the work, i.e., the purpose, breadth, and depth of the assignment, and the effect of work products or services both within and outside the organization. A score of one indicates that the work involves routine, simple tasks, and that the output has little impact beyond the immediate organizational unit or beyond the service provided to others. A score of six indicates that the work requires planning and organization, and that the output is vital to the overall organization or affects large numbers of people. Again, this skill may complement IT use since a high score indicates cognitive, non-routine work.

6. Personal contact (1-4): measures the contacts with persons outside the supervisory chain, in terms of what is required to make the initial contact, the difficulty of communicating with those contacted, and the setting in which the contact takes place. A score of one indicates that contacts are with other employees within the immediate organizational unit or with the general public under highly structured settings. A score of four indicates that contacts are with high-ranking officials from outside the establishment in highly unstructured settings. This skill is one measure of interpersonal skills required for the job.
7. Purpose of contacts (1-4): measures the difficulty or sensitivity of the nature of the contact. A score of one indicates that purpose of contacts is to obtain or convey information. A score of four indicates that the purpose of contacts is to justify, defend, negotiate or settle matters involving significant or controversial issues. This factor is another measure of the interpersonal skills required for the job. It is the skill most closely related to the "interactive tasks" as first used by Autor, Levy, and Murnane (2003) or "influence skills" used by Green et al. (2007). Prior evidence suggests this skill should be a complement to computer use. We hypothesize further that it may be positively related to the use of communications applications.
8. Physical demands (1-3): measures the physical skill and exertion demanded by the work. A score of one indicates that the work is largely sedentary. A score of three indicates that the work requires considerable and strenuous physical exertion or heavy lifting. Other researchers (e.g. Autor, Levy, and Murnane 2003) have found that computers tend to substitute for "routine manual tasks", but are not as good at substituting for non-routine, manual tasks. Thus, while we do not expect that a

desktop computer will increase the productivity of a worker whose tasks involve heavy lifting, a factory worker's productivity may be enhanced by the use of computerized robots. Entorf, Gollac, and Kramarz (1999), however, found no significant effects for using robots.

9. Work environment (1-3): measures the risks and discomforts of the physical surroundings or the work. A score of one indicates that the job setting contains everyday risks and discomforts that require normal safety precautions. A score of three indicates that the job setting contains high risks, potentially dangerous situations or unusual stress, which may require advanced safety precautions. This variable is an aspect of a job, not a skill. We include it as an additional control variable in our analyses because wages should be higher for those willing to assume job risks

B. CPS Computer and Internet Supplement

We first link the skill data to two CPS supplements (October 1997, October 2003) that ask respondents to answer extensive questions about computer and/or internet use. Our sample for these analyses includes non-agricultural, private sector wage and salary employees aged 18–64 in the outgoing rotation group (ORG) [about one-fourth of the sample], because this is the group of individuals for whom we have relevant earnings measures.[7] In addition, we exclude those working in private households because they are excluded from the WES. Workers are asked to report earnings only for their main job. For workers paid by the hour, we use their

[7] We also exclude 9 occupations for which the NCS does not record job skills. This affects only 41 individuals. These occupations include legislators, dancers, artists, athletes, authors, actors, musicians, painters, and announcers.

hourly rate of pay as our hourly wage measure.[8] For non-hourly workers, we calculate the hourly wage using usual weekly earnings and usual hours worked.[9] We exclude workers with hourly wages less than $2.80/hour or greater than $250/hour. Our dependent variable in the analyses is the natural logarithm of hourly wages. Approximately 3 percent of our sample is missing wages. We use the CPS outgoing rotation weights for all analyses on these data. Our sample for 1997 includes 9,139 workers, which drops to 8,718 when we include information on job skills because of confidentiality reasons. Our sample for 2003 includes 10,571 workers, which drops to 9,652 when we include information on job skills.[10]

The CPS Computer and Internet Use supplements have detailed information on computer use and software applications that has been used in numerous papers (e.g. Krueger 1993; Tashiro; Valletta 2006). We describe the CPS supplement questions in order to compare them with the Canadian questions. Employees were asked if they use a computer for their main job only. By a computer, we are referring to a desktop computer or mainframe computer as opposed to other computerized technologies. In October 1997, about 51% of U.S. workers used a computer on their main job (Table 1). By October 2003, about 53% of U.S. workers used a computer. Computer users were also then asked what types of software applications they used. They were asked if they used any of the following six groups of software applications: word processing or desktop publishing, internet or e-mail, calendar or scheduling, spreadsheets or databases, graphics and design, and programming.

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[8] About 2/3 of the workforce is paid hourly.

[9] Note that workers could report their usual earnings over any period of their choosing. For example, weekly earnings were top-coded at $1,923 in 1997 and then at $2,884.61 from 1998 forward. We multiply the top-coded values by a factor of 1.5.

[10] With the 2003 CPS, the occupation and industry coding changed so it was necessary to map codes back into the 1990 Census occupation code and major SIC used by the NCS.

In Table 1, we describe the proportion of workers using these different software applications. In 1997, word processing and desktop publishing are used by 27% of the sample, followed closely by internet and e-mail applications (24%), spreadsheets and databases (22%), and calendar and scheduling applications (18%). A much smaller proportion of the sample use graphics (10%) and programming (8%) applications. By 2003, internet and e-mail applications were the most widely used applications (38% of the sample), followed by word processing (34%), spreadsheets (34%), and calendars (31%). Even though the percentage of computer users did not rise dramatically, individual computer users were using their computers for a greater variety of tasks. In 1997, the mean number of different software categories used was 2.2, conditional on using a computer (and 1.1 unconditionally). In 2003, the mean number of different software categories, conditional on computer use, was 3.0 (and 1.6 unconditionally).

C. The Canadian WES and Technology Questions

The WES is an ongoing restricted-access survey that began collecting data annually in 1999. The WES is an employer-employee linked data set. Establishments were first selected from employers in Canada with paid employees in March of that 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). The initial sample was followed for eight more years, with new establishments (births) being added every two years to maintain sample representativeness. Within an establishment, up to twenty-four employees were sampled and followed for two years; however, in 2006, employees were not re-interviewed.

Therefore, we only use data form 1999–2004, which includes three sets of two-year panels of employees.[11] These data allow us to control for a rich set of observable individual and establishment characteristics as well as unobservables, such as an individual's ability to learn to use new technology, which may affect both computer use and wages. We match 1997 NCS skills with the 1999–2000 WES, the 2002 NCS skills with the 2001–2002 WES, the 2003 NCS skills with the 2003 WES, and the 2004 NCS skills with the 2004 WES.[12]

In the compensation section of the WES, employees reported their wage or salary before taxes and other deductions in any frequency they preferred (e.g., hourly, daily, weekly, annually). Unlike in the CPS data, wages were not top-coded. In our analysis, we use the hourly wage created by Statistics Canada, who divided the wage or salary by the appropriate frequency.

In addition to information on a rich set of establishment characteristics, the WES also has more detailed information about the use of computers, software applications, and other information technologies used by workers than those in the CPS Supplement. They also have more details about how intensively the computer is used. The panel nature of the data set also allows us to identify the short-run returns to adopting new technologies.

Our main computer use variable comes from the question: "Do you use a computer in your job? Please exclude sales terminals, scanners, machine monitors, etc." A help screen further clarified: "By computer, we mean a microcomputer, minicomputer, or mainframe computer that can be programmed to perform a variety of operations." In 1999, 62% of the sample used a computer (Table 2). In 2003, 65% of the sample used a computer, 12% more than

[11] In establishments with fewer than four employees, all employees were selected.
[12] We are still waiting for data to be available from 1999-2001.

in the U.S (the difference may be partly due to measuring computers on all jobs instead of main job only). By 2004, 68% of the sample was using a computer. Workers were also asked how long they have used a computer in any workplace. They were asked to freely report any software applications they used, which were grouped into 14 categories by interviewers, and then to specify their most frequently used software applications. Therefore, we can determine in more detail than in the CPS how the computer is used to enhance the worker's job. In Table 2, we describe the proportion of Canadian workers using each of these software applications over time. In 1999, the most commonly used application was word processing, with 35 percent of workers using this application. By 2004, 44 percent of workers were using word processing as well as communications software, such as the internet and e-mail. There was growth in the use of all of the applications from 1999–2004, with especially high jumps in usage associated with increased computer use from 2001–2003. In 2004, spreadsheets were used by 38% of the sample, followed closely by databases (33%) and specialized office (32%). Similar to the U.S., a much smaller proportion of the sample used graphics (17%) and programming (6%) applications. In addition, 13% used data analysis applications, 14% used management applications, and 9% used desktop publishing. In 1999, the mean number of software applications reported, conditional upon computer use was 2.6 and by 2004 it was 4.0.

Workers are asked separately about using computer-aided technologies, such as industrial robots and retail scanning systems, and other technologies, such as cash registers, sales terminals, and scanners. These other technologies are especially likely to substitute for routine tasks and not likely to require advanced cognitive skills for use (Zoghi and Pabilonia 2007). Approximately 13% of worker used computer-aided technologies and 26% of workers used other technologies.

D. Descriptive Analysis

Table 3 presents the descriptive statistics for the CPS variables and linked NCS job skills used in our analyses, by computer use status. We find many significant differences between computer users and non-users in the U.S. In 1997, those who use computers earn 53% more than non-users while in 2003 they earn 55% more than non-users. Skill requirements for the jobs held by computer users are significantly different from those for jobs held by non-users Computer users hold jobs that require significantly higher levels of knowledge, receive less supervision, require using greater personal judgment in following guidelines, are more complex and require higher personal skills than non-users. Between 1997 and 2003, computer users' scores fell in all of these skills, which is consistent with a model of technology diffusion where those with the highest skills are given a computer to use first (e.g. Borghans and ter Weel 2004). Computer users are less likely to hold jobs that are physically demanding or whose work environment involves risks or discomforts than non-users. They are also much better educated. They are less likely to be black or Hispanic. They are more likely to work full-time, live in a metropolitan statistical area (MSA), be married and be female. They are less likely to be union members.

In Table 4, we present similar descriptive statistics for the WES variables. From 1999–2004, the earnings of computer users compared to non-users rose each year, from 40% more in 1999 to 59% more in 2004. Job skill scores for computer users and non-users in Canada are remarkably similar to those for U.S. workers. Similar to the U.S., between 1999 and 2004, computer users' scores all fell in the first seven skill categories, which measure cognitive and interactive skills. Over the period 1999–2004, there is little change in skill scores in these establishments. Computer users and non-users were equally likely to be non-European in most years. From 1999–2002, users were more likely to speak the same language at work and at home. They also had greater tenure at their establishment, worked in larger establishments, and worked in establishments with a higher proportion of computer users. Users had much higher years of computer experience than non-users. In 1999, users had on average 8.64 years of computer experience while non-users had only 1.53 years on average. By 2004, computer users had almost 12 years of computer experience. Similar to computer users in the U.S., they were more likely to work full-time, be married, and be female. They were less likely to be union members.

III. Estimation and Results

We examine the returns to IT use and adoption using several different econometric techniques.

A. Returns to General Computer Use/Adoption and Skills

In order to estimate the returns to desktop computer use, we begin by estimating a standard Mincerian wage equation augmented by a computer use indicator, similar to Krueger (1993):

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

where W is individual *i*'s hourly wage at time *t*; X_i is a vector of observable individual characteristics of *i* (as well as any workplace attributes to which *i* is linked in the WES) at time *t*; $Comp_{it}$ is a binary variable indicating that individual *i* used a computer use at time *t*; α_t, β, γ are parameters to be estimated; and ε_{it} is a stochastic disturbance term assumed to follow a normal distribution.

The return to computer use from this model has been criticized as being subject to omitted variable bias, due to unobserved learning ability or a worker's skill level. We attempt to minimize this bias in several ways. First, we add successively detailed occupation dummies.[13] Then, we replace these dummies with the job skills that these occupations require. Levenson and Zoghi (2007) show that while occupation indicators do proxy for job skills to some extent, there remains substantial skill variation within even the most detailed occupation categories, and that the variation is higher for managerial and professional occupations than for blue collar ones. In the WES, we have a panel of establishments and three matching panels of employees within those establishments. When looking at the returns to general computer use with the WES, we can control for establishment fixed-effects to remove time-invariant unobserved establishment-level heterogeneity.

In column 1 of Table 5, we first present the return to computer use using the 1997 CPS Supplement for a specification similar to that used by Krueger (1993); however, a significant difference is that we measure education in broad categories (less than high school, high school degree, some college, bachelor's degree, and graduate degree) rather than the number of years of schooling in order to allow for nonlinearities in returns to education. Other control variables included are potential experience and its square (measured as age – years of schooling – 6), black, other race, Hispanic, part time worker, lives in metropolitan statistical area, veteran status, union member, female, married, female interacted with married, Census region and a constant.

[13] Krueger (1993) notes that it is unclear whether occupation dummies are appropriate when estimating the returns to computer use because computer skills might help workers qualify for jobs in better paying occupations or industries.

In order to measure the percentage effect of computer use on wages, it is necessary to transform the coefficients using 100*(exp(γ) – 1). The return to computer use in 1997 is 22 percent. In column 2, we add controls for detailed occupations (3-digit) and ten major industries. The return falls to 10 percent. We then replace these industry and occupation controls with controls for our 9 job skills, which are linked to the CPS Supplement by three-digit occupation and major industry codes. The return to computer use is 11 percent. Therefore, these skills control for most of the observed wage differences between occupations. Not surprisingly, workers earn significantly higher wages if they have higher scores on the following job skills independent of computer use: knowledge, guidelines (meaning the job requires more autonomy), scope and effect, and work environment. They earn less if their job involves manual tasks (measure by physical demands), perhaps capturing differences in wages between white-collar and blue-collar jobs. The wage return for earning either a bachelor's degree or a graduate degree falls dramatically when we add detailed controls for occupation and industry or our matched skills. In addition, the return to a graduate degree falls 4 percent when we use job skills rather than occupation controls.

However, including job skill indicators rather than occupation indicators and, more importantly, these skills interacted with computer use, allows us to ask what job skills are complementary to computer use and what is the return to computer skills (as proxied by computer use) at the average skill level. In column 4, we present estimates for returns to computer use and skills from this specification, where the skills have been demeaned prior to interacting them.[14] Throughout the paper, we include interactions of skills with IT use for all skills, with the exception of work environment which we do not expect to be related to computer

[14] The demeaned skill is the difference between the occupation/industry specific median and the full sample median.

skills. We find a decrease in the overall return to computer use to 5%. Table 7 shows estimates for the interaction effects. We find that workers whose jobs are more autonomous (measured by supervision received) and require greater people skills than the average job (measured by purpose of contacts) earn higher wages when using a computer. A test of the joint effect of computer use and its interaction with purpose of contacts is significant at the 1% level. Our results using the 2003 CPS differ slightly (columns 5-8 in Table 5). Overall returns to computer use are lower in each specification, with the exception of the regression including interaction effects, while returns to education are higher. As in 1997, workers earn significantly higher wages if they have higher scores on knowledge, non-routine work (i.e. scope and effect), and work environment (column 7). In addition, they now earn a return to people skills (as measured by personal contacts). In column 8, where we interact skills with computer use, we find a large significant main effect of computer use on wages (13%). Computer use is complementary to more autonomy on the job, non-routine work in 2003 (measured by scope and effect), and personal contacts (Table 7). Surprisingly, the effect of computers on job complexity and knowledge is negative in 2003. Thus, in the CPS, we find some evidence that computers, in general, complement workers who perform non-routine tasks as well as those tasks that require interactive skills.

Using the WES, we first estimate pooled cross-sections using the 1999, 2001, and 2003 data (Table 6).[15] In column 1, we present the returns to computer use for a basic specification similar to the one estimated using the CPS (see column 1 of Table 5). Control variables include education levels, potential experience and its square, indicators for part-time, married, female, female interacted with married, union member, region, year, and a constant. The return to

[15] We estimated pooled cross-sections so that we can also control for establishment fixed-effects.

computer use in the WES is slightly higher than the CPS, at 27% compared to 22%. In column 2, we add some additional variables from the WES that may help explain wage growth, but are unavailable in the CPS. These include indicators for non-European background and language spoken being different in work and home, ln(establishment size), percentage of computer users in the establishment, and years of job tenure and its square. The coefficient estimates for these additional variables are highly significant (estimates available from authors). In addition, we include indicators for computer-aided technologies, such as industrial robots or retail scanning systems, and other technology devices, such as cash registers.[16] The return on desktop computer use falls to 16%. The return on computer-aided technologies is negative 2% and negative 5% on other devices. In column 3, we add controls for detailed occupations and major industries. The return on desktop computer use then falls to 10%, which is identical to the return in the CPS. The return on computer-aided technologies is 1% and the return on other devices is negative 2%. We then replace occupations and industries with our nine job skills. Because not all of the occupations could be matched to job skills, the sample size is reduced to 58,227. The return to desktop computer use is 7%. We further take advantage of the matched employer data by controlling for establishment fixed effects in column 5. The return to desktop computer use falls to 5% and the return to computer-aided technologies is still 1%, which is in contrast to previous research (Entorf, Gollac, and Kramarz 1999). In addition, the return to physical demands changes from a negative to a positive, which suggests that we were previously not adequately controlling for differences in compensation between establishments. According to the theory of compensating differentials, workers should receive higher wages for physical stress, all else equal.

[16] Coefficient estimates on desktop computer use are robust to the exclusion of these other computerized technologies.

In column (6), we add years of computer experience and its square to the specification. We find that all desktop computers users earn slightly higher wages than non-users (2%), but more experienced users earn even higher returns, which is consistent with findings in Pabilonia and Zoghi (2005) and Zoghi and Pabilonia (2007). Alternatively, in column (7), we present estimates for returns to computer use (of average experience level) and skills (previously demeaned) when we allow the return to computer use to vary by job skill requirements. We also allow the return to other computerized technologies to vary by job skill requirements. The main effect for desktop computer use is 7% for a worker with average job skills. There is no main effect for other computerized technologies for a worker with average job skills. In the WES, workers earn significant returns to higher than average scores on knowledge, complexity, scope and effect, personal and purpose of contacts, and work environment. Supervision received has a significant negative effect in the WES.

The final column in Table 7 presents estimates for the interaction effects for specification using the WES data. As in the CPS, we find that computer users whose jobs are more autonomous (measured by supervision received) earn higher wages when using a computer. We also find complementary effects for those using interactive skills. Unlike in the CPS, we find that workers with more knowledge get a small, but significant wage boost from using a computer. Contrary to our initial hypotheses, but consistent with the 2003 CPS, we find that those workers in the WES whose jobs are more routine (measured by complexity) earn higher wages when using a computer than workers with more complex jobs who use a computer. Also, contrary to hypothesized, we find that computer use is complementary to greater than average physical demands on the job. Perhaps, we are just capturing differences between managers who use desktop computers and non-managers in physically demanding jobs. We also find that physical demands are complementary to computer-aided technologies and other devices. A joint test of the main effect of computer-aided technologies and its interaction with physical demands indicates a positive effect on wages for those with greater than average physical demands on the job.

One way to address a potential omitted variable bias problem is by using the employee-panel in the WES. We can estimate a flexible first-differenced model, as used by Zoghi and Pabilonia (2005) and Dolton and Makepeace (2004), which allows us to control for unobservable time-invariant worker heterogeneity and at the same time allows for varying effects among new adopters, long-term computer users, and those who stop using a computer, compared to never users. Specifically, we can difference the following two equations:

$$\ln W_{it} = \alpha_t + \beta X_{it} + \gamma^m{}_t M_i + \gamma^c{}_t C_i + \delta_i + \varepsilon_{it} \qquad (2)$$

$$\ln W_{it+1} = \alpha_{t+1} + \beta X_{it+1} + \gamma^m{}_{t+1} M_i + \gamma^a{}_{t+1} A_i + \delta_i + \varepsilon_{it+1} \qquad (3)$$

in order to estimate the following first-differenced model:

$$\Delta \ln W_i = \Delta\alpha + \beta \Delta X_i + (\Delta\gamma^m) M_i + \gamma^a{}_{t+1} A_i - \gamma^c{}_t C_i + \Delta\varepsilon_i \qquad (4)$$

where Δ is the change in each variable/coefficient between t and t+1; M_i, A_i, C_i are indicator variables for maintaining computer use, adopting a computer, and ceasing to use a computer, respectively. The return to computer use varies over time for continued users when $\gamma^m{}_t \neq \gamma^m{}_{t+1}$.

However, this model restricts the remaining coefficients to being the same in each difference. Therefore, following Zoghi and Pabilonia (2007), we restrict the WES sample to only those who could adopt computers and estimate the following first-differenced model using OLS:

$$\Delta \ln W_{it} = \alpha + \beta \Delta X_{it} + \gamma \Delta Comp_{it} + \mu \Delta Year2000_{it} + \eta \Delta Year2002_{it} + \Delta \varepsilon_{it} \quad (5)$$

where ΔX_{it} includes time-varying controls, $Year2000_{it}$ and $Year2002_{it}$ are binary variables equal to one if the individual was interviewed in 2000 or 2002, respectively, and zero otherwise (these variables allow us to control for wage growth differences between panels); α, β, γ, μ, and η are parameters to be estimated. [17] When estimating this specification, we include only workers who do not change establishments and thereby also minimize concerns about the importance of establishment-level unobserved heterogeneity. The effects from this specification measure the short-run returns to extending the technology to those who do not currently use a computer rather than the previously measured returns, which were returns for the average computer user.

Results for specification (5) are reported in Table 8. The return in each column is a short-term return to computer adoption conditional upon being able to adopt (i.e. not already using one in the first year of each employee panel). We include the standard controls that change over time.[18] We also include controls for changes in skills associated with the worker changing occupations within the establishment and an indicator for whether the worker was promoted, which both help to control for the potential endogeneity of adopting a computer as part of an internal job change. Additionally, we include establishment fixed-effects to control for characteristics of the establishments that affect wage growth. Our sample size includes 29,394 worker-year observations with matched skills. Previous research by Zoghi and Pabilonia (2007), who used a similar specification with the exception that they controlled for changes in major occupations rather than skills and covered the period 1999–2002, found a return of about 3.6% in

[17] When we do estimate specification 4, we find that the wage return to adopters and continuing users is about the same over a year, but there is no corresponding wage loss for those who no longer use a computer (estimates available upon request).
[18] We exclude controls for changes in the use of other computerized technologies in this specification, but will look at returns to adopting these other technologies for non-users in separate specifications in a future draft.

the first year of adoption conditional upon not using a computer in the first year. In column 1, we find 2.6% higher wage growth for computer adopters. In column 2, we then control for the interaction of our second year job skills with adopting a computer in order to estimate how adopting a computer and having a certain skill level (demeaned) affects wage growth. The main return to adopting a computer is now 5% for the average worker. None of the skill interaction effects is significant; however, a joint test of the main plus interaction effect reveals significant positive returns to adopting a computer if the worker's job requires greater than average levels of knowledge, supervision received, guidelines, scope and effect, or personal contacts.

In a future version of this paper, we will examine those who adopted other technologies, as we did previously with adopting desktop computers, where we restrict the sample to employees who did use the other technologies in the first year of each panel.

B. Return to Software Application Use/Adoption and Skills

In this section, we take further advantage of the detailed computer use questions in the WES. We examine how the return to using a desktop computer for the worker's most frequently used software application varies by skill levels. We estimate a specification similar to equation (1) where we replace the computer use indicator with a vector of main software application indicators. Specifically, we include a vector of fourteen computer applications: word processing, specialized office, databases, spreadsheets, communications, expert systems, management applications, graphics, computer-aided design, programming, desktop publishing, data analysis, computer-assisted engineering, or other IT. In all of our specifications, we also include establishment fixed-effects. In the first column of Table 9, we control for job skills. We find considerable variation in the returns to main software application used where the comparison group is non-computer users.[19] A worker using programming applications as their main application earns 7% more than a non-computer user. Those using communications and e-mail as the main application have 16% higher wages compared to non-computer users. It is hard to imagine that the highest return for workers is from using e-mail or the internet because these tools are relatively easy to learn; however, businesses have benefited tremendously from using the internet to lower costs throughout their production processes and, therefore, workers in these businesses might share in these gains (Lee and Kim 2004).

Therefore, in a third specification (column 3), we allow the return to using these applications to vary by job skills, which have been demeaned. We still find that there is a large return (13%) to using the e-mail and internet (i.e. communications) *per se* for the average skilled worker. In addition, we find that these communications applications are complementary to both personal contacts and purpose of contacts (see Table 10 for selected interaction effects). This latter finding is the first that we are aware of that shows that the return is not only to knowing how to e-mail *per se*, but that e-mail enhances the productivity of workers whose jobs require above average communication skills. We also find that communications applications are complementary to autonomy on the job (as measured by supervision received) and surprisingly, physical demands on the job. The return to communications and word processing are higher for relatively more routine jobs than non-routine jobs, as measured by complexity. We find that word processing applications when used as the primary computer application are complementary

[19] We similarly ran regressions using the first two most frequently used applications. Results are qualitatively similar, but lower in magnitude, as might be expected because the second tool is probably not as important to the job. We also ran a specification where we included indicators for the use of any application. Again, results are similar, but lower in magnitude.

to knowledge skills, interpersonal skills, and autonomy on the job. We do not find that programming applications are complementary to any job skills (Table 11).

In Table 12, we present results for the short-run returns to adopting a computer and a specific application as the main application, compared to not adopting a computer, from an estimation using first-differences.[20] The return is a short-turn return for adopting the computer and the application. In column 1, we control for the standard controls and changes in skills. We find significant wage returns in the first-year of adopting database, management, specialized office, and computer-assisted engineering applications, but not communications applications. These applications are likely to require or complement critical thinking skills, with perhaps the exception of specialized office applications.

In column 2, we control for the interaction between 2nd year demeaned skill levels and computer applications adopted. We find that workers with average skill levels who adopt a computer and use database applications earn 14 percent more after one year than those who do not adopt a computer. Similarly, workers with average skill levels who adopt a computer and use management applications earn 17 percent more after one year than those who do not adopt a computer. In Table 13, we present estimates for the interaction of adopting three applications (communications, management, and computer-assisted engineering) and skills. There are no significant interaction effects for word processing, as we found in the cross-sectional results, nor were there significant effects for programming by skill level. We find that adopting communications applications when used as the primary computer application are complementary

[20] We also estimated a specification using three indicators for adopting a computer and the amount of work time spent on the computer. Results (not shown here but available upon request) indicate that workers who use the computer for more of their work day get a higher wage boost from adopting a computer.

to interpersonal skills, as measured by personal contacts. Management applications are complementary to a higher than average skill on scope and effect (meaning importance to the organization) and to personal contacts (meaning the contacts are outside the immediate work group), which are both skills important to upper management. Computer-assisted engineering applications are complementary to knowledge skills and complexity on the job.

V. Conclusion

In this paper, we have examined the returns to numerous types of IT use and adoption in North America and how those returns vary by skill level required on the job. When controlling for a common set of nine job skills across occupations, we still find a significant return to computer use *per se* for the average worker in both the U.S and Canada. We also find evidence that workers earn higher wages if they use a computer and their job requires more autonomous decision-making or interactive tasks than the average job, which is consistent with previous researcher’s findings. Results for our OLS wage regressions are similar enough across datasets to justify our use of the set of U.S. job skills with the Canadian data. In addition, the Canadian data allows us to explore the importance of skills and more detailed information on computer applications, while also controlling for unobserved establishment-level and individual-level heterogeneity. We find that Canadian workers earn a return to adopting a computer among current non-users with average job skill requirements of about 5%.

Previous researchers have found that the average worker earns a return to using e-mai. By including detailed information on job skills in a wage regression and controlling for establishment-level fixed effects, we are able to empirically demonstrate that the return is not solely a return to e-mail skills but additionally workers whose jobs require them to do more interactive tasks earn a higher wages if they use the internet and e-mail. When we further control for individual-level fixed effects, we also find that workers who adopt communications applications as their main software application earn a return in the first year because it complements interactive tasks. We also find that interactive tasks are complementary to word processing. The ability to work autonomously is complementary to both communications applications and word processing. Surprisingly, we do not find that programming applications are complementary to any job skills. We also find that using computer-aided technologies, such as industrial robots, are complementary to performing physically-demanding tasks.

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Table 1. Proportion Using Computers, by Software Type (October CPS Supplement)

	1997	2003
Any computer use	0.51	0.53
Word processing or desktop publishing	0.27	0.34
Internet and e-mail (communications)	0.24	0.38
Calendar or scheduling	0.18	0.31
Spreadsheets or databases	0.22	0.34
Graphics and design	0.10	0.14
Programming	0.08	0.08
No. of Observations	9,139	10,571

Note: The proportion of respondents who used various computer applications may exceed 1 since they may report using multiple applications.

Table 2. Proportion Using Computers, by Application Type (WES)

	1999	2000	2001	2002	2003	2004
Any computer use	0.61	0.64	0.60	0.63	0.65	0.68
Word processing	0.35	0.38	0.34	0.39	0.41	0.44
Spreadsheets	0.25	0.29	0.26	0.32	0.34	0.38
Databases	0.18	0.21	0.20	0.27	0.27	0.33
Desktop publishing	0.04	0.04	0.04	0.08	0.08	0.09
Management applications	0.05	0.07	0.06	0.11	0.12	0.14
Communications	0.19	0.27	0.23	0.34	0.37	0.44
Specialized office	0.21	0.23	0.24	0.29	0.32	0.32
Graphics	0.08	0.08	0.09	0.15	0.14	0.17
Data analysis	0.04	0.04	0.04	0.11	0.10	0.13
Programming	0.02	0.02	0.03	0.05	0.05	0.06
Computer-assisted design	0.02	0.02	0.02	0.04	0.04	0.06
Computer-assisted engineering	0.01	0.01	0.01	0.02	0.02	0.02
Expert systems	0.02	0.02	0.02	0.02	0.03	0.07
Other Software Application	0.14	0.12	0.09	0.08	0.07	0.05
Computer-aided technologies	0.12	0.15	0.14	0.13	0.13	0.13
Other technologies	0.27	0.26	0.23	0.26	0.26	0.26
No. of Observations	23,540	19,364	20,352	15,669	20,834	15,814

Table 3: Descriptive Statistics, by Computer Use Status (CPS Supplement)

	1997			2003		
Variables	All	User	Non-User	All	User	Non-User
Hourly wage	13.38	**16.16**	**10.54**	17.20	**20.61**	**13.31**
Job Skills (N=8,723)				(N=9,652)		
Knowledge	3.73	**4.57**	**2.87**	3.73	**4.42**	**2.91**
Supervision Received	2.36	**2.68**	**2.03**	2.32	**2.56**	**2.05**
Guidelines	2.07	**2.37**	**1.75**	2.03	**2.27**	**1.75**
Complexity	2.41	**2.72**	**2.09**	2.40	**2.63**	**2.13**
Scope and Effect	2.13	**2.43**	**1.82**	2.06	**2.29**	**1.79**
Personal Contacts	1.73	**2.10**	**1.34**	1.66	**1.98**	**1.30**
Purpose of Contacts	1.46	**1.73**	**1.19**	1.46	**1.69**	**1.19**
Physical Demands	1.60	**1.34**	**1.86**	1.59	**1.36**	**1.85**
Work Environment	1.47	**1.23**	**1.73**	1.45	**1.24**	**1.70**
Education Level						
Less than High School	0.12	**0.03**	**0.21**	0.11	**0.03**	**0.20**
High School Degree	0.35	**0.26**	**0.44**	0.33	**0.24**	**0.43**
Some College	0.30	**0.34**	**0.25**	0.20	**0.32**	**0.28**
Bachelor's degree	0.18	**0.28**	**0.08**	0.19	**0.29**	**0.07**
Graduate degree	0.06	**0.09**	**0.02**	0.07	**0.11**	**0.02**
Potential Experience	17.99	17.73	18.25	19.27	19.52	18.98
Race/ethnicity						
Non-Hispanic black	0.11	**0.08**	**0.14**	0.10	**0.08**	**0.13**
Non-Hispanic other	0.04	0.04	0.04	0.06	**0.07**	**0.05**
Hispanic	0.11	**0.06**	**0.16**	0.14	**0.09**	**0.21**
Part time	0.15	**0.10**	**0.19**	0.15	**0.12**	**0.19**
Married	0.58	**0.63**	**0.53**	0.57	**0.61**	**0.51**
Female	0.46	**0.53**	**0.39**	0.46	**0.53**	**0.38**
Lives in MSA	0.83	**0.87**	**0.79**	0.83	**0.86**	**0.80**
Union member	0.10	**0.06**	**0.13**	0.09	**0.07**	**0.11**
Veteran	0.09	**0.08**	**0.10**	0.08	0.07	0.08
Region						
Northeast	0.20	0.20	0.20	0.19	**0.20**	**0.18**
Midwest	0.25	0.25	0.24	0.24	0.24	0.24
South	0.34	0.33	0.35	0.34	0.34	0.35
West	0.22	0.22	0.21	0.22	0.22	0.22
Observations (All except skills)	9,139	4,631	4,508	10,571	5,579	4,812

Means in bold are significantly different at the 5% level.

Table 4. Descriptive Statistics, by Computer Use Status (WES)

	1999		2000		2001		2002		2003		2004	
	User	Non-User	User	Non-User	User	Non-User	User	Non-User	User	Non-User	User	Non-User
Hourly wage	**20.83**	**14.83**	**21.78**	**15.21**	**22.46**	**14.93**	**23.75**	**15.38**	**23.54**	**15.08**	**24.83**	**15.67**
Job Skills												
Knowledge	**4.58**	**2.88**	**4.53**	**2.87**	**4.39**	**2.74**	**4.46**	**2.75**	**4.40**	**2.69**	**4.47**	**2.71**
Supervision Received	**2.69**	**2.01**	**2.70**	**2.03**	**2.55**	**1.94**	**2.58**	**1.95**	**2.58**	**1.95**	**2.60**	**1.97**
Guidelines	**2.29**	**1.67**	**2.28**	**1.70**	**2.22**	**1.68**	**2.25**	**1.69**	**2.24**	**1.65**	**2.24**	**1.68**
Complexity	**2.68**	**2.10**	**2.69**	**2.12**	**2.61**	**2.05**	**2.63**	**2.04**	**2.60**	**2.02**	**2.63**	**2.03**
Scope and Effect	**2.39**	**1.79**	**2.40**	**1.82**	**2.33**	**1.79**	**2.37**	**1.80**	**2.32**	**1.74**	**2.35**	**1.78**
Personal Contacts	**2.11**	**1.36**	**2.11**	**1.35**	**2.03**	**1.32**	**2.04**	**1.33**	**2.01**	**1.29**	**2.00**	**1.29**
Purpose of Contacts	**1.67**	**1.21**	**1.69**	**1.21**	**1.66**	**1.18**	**1.68**	**1.19**	**1.64**	**1.17**	**1.66**	**1.17**
Physical Demands	**1.34**	**1.86**	**1.35**	**1.88**	**1.32**	**1.88**	**1.32**	**1.88**	**1.35**	**1.91**	**1.35**	**1.91**
Work Environment	**1.21**	**1.72**	**1.22**	**1.74**	**1.23**	**1.77**	**1.23**	**1.76**	**1.22**	**1.77**	**1.23**	**1.77**
Education Level												
Less than High School	**0.05**	**0.19**	**0.06**	**0.19**	**0.05**	**0.22**	**0.06**	**0.22**	**0.04**	**0.21**	**0.04**	**0.21**
High School Degree	**0.15**	**0.22**	**0.15**	**0.22**	**0.14**	**0.24**	**0.14**	**0.26**	**0.14**	**0.23**	**0.13**	**0.24**
Some College	0.53	0.51	0.53	0.51	**0.55**	**0.47**	**0.54**	**0.46**	**0.56**	**0.49**	**0.56**	**0.50**
Bachelor's degree	**0.17**	**0.06**	**0.17**	**0.06**	**0.18**	**0.04**	**0.18**	**0.04**	**0.17**	**0.04**	**0.18**	**0.04**
Graduate degree	**0.09**	**0.02**	**0.09**	**0.02**	**0.08**	**0.02**	**0.08**	**0.02**	**0.08**	**0.02**	**0.08**	**0.01**
Non-European	**0.13**	**0.15**	0.13	0.14	0.15	0.16	0.15	0.15	0.19	0.18	0.18	0.17
Different language work and school	**0.07**	**0.10**	**0.07**	**0.10**	**0.10**	**0.13**	**0.10**	**0.13**	0.10	0.10	0.10	0.10
Part-time	**0.16**	**0.29**	**0.14**	**0.26**	**0.15**	**0.32**	**0.16**	**028**	**0.15**	**0.34**	**0.14**	**0.30**
Married	**0.60**	**0.52**	**0.61**	**0.54**	**0.57**	**0.49**	**0.59**	**0.53**	**0.58**	**0.46**	**0.62**	**0.48**
Female	**0.55**	**0.48**	**0.55**	**0.47**	**0.54**	**0.45**	**0.53**	**0.46**	**0.56**	**0.47**	**0.55**	**0.46**
Tenure	**8.74**	**7.94**	**9.50**	**8.75**	**8.59**	**7.35**	**9.47**	**8.30**	**9.16**	**7.07**	**9.91**	**7.92**
Ln(establishment size)	**4.48**	**3.88**	**4.42**	**3.90**	**4.50**	**3.86**	**4.50**	**3.81**	**4.54**	**3.78**	**4.59**	**3.75**
% of computer users in establishment	**0.60**	**0.24**	**0.64**	**0.33**	**0.65**	**0.27**	**0.66**	**0.28**	**0.64**	**0.28**	**0.64**	**0.29**
Yrs. of computer experience	**8.64**	**1.53**	**9.67**	**1.68**	**9.62**	**1.38**	**10.28**	**1.64**	**10.89**	**1.80**	**11.64**	**2.34**
Union member	**0.24**	**0.35**	**0.25**	**0.37**	**0.24**	**0.30**	**0.26**	**0.32**	**0.24**	**0.30**	**0.24**	**0.31**
No. of Observations	14,352	9,188	12,443	6,921	12,242	8,110	9,886	5,783	13,607	7,227	10,711	5,103

Notes: User and non-user means in bold are significantly different at the 5% level.

Table 5. OLS log hourly wage regressions (CPS Supplement)

	1997				2003			
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Computer use	0.198***	0.086***	0.103***	0.050**	0.161***	0.073***	0.086***	0.120***
	(0.011)	(0.013)	(0.013)	(0.025)	(0.012)	(0.012)	(0.013)	(0.032)
Knowledge			0.045***	0.053***			0.046***	0.067***
			(0.008)	(0.013)			(0.009)	(0.014)
Supervision received			0.019	-0.029			-0.025	-0.085***
			(0.016)	(0.022)			(0.020)	(0.029)
Guidelines			0.074***	0.085***			0.026	0.053
			(0.017)	(0.024)			(0.024)	(0.035)
Complexity			-0.013	-0.0001			0.003	0.049*
			(0.014)	(0.021)			(0.019)	(0.028)
Scope and Effect			0.033**	0.051**			0.067***	0.026***
			(0.018)	(0.026)			(0.023)	(0.034)
Personal Contacts			0.015	0.031			0.070***	0.015
			(0.014)	(0.023)			(0.016)	(0.033)
Purpose of Contacts			0.021	-0.019			0.014	0.016
			(0.016)	(0.029)			(0.018)	(0.032)
Physical Demands			-0.026**	0.009			-0.018	0.016
			(0.017)	(0.029)			(0.019)	(0.032)
Work Environment			0.037**	0.038**			0.041**	0.033*
			(0.017)	(0.018)			(0.017)	(0.018)
High school degree	0.159***	0.128***	0.132***	0.135***	0.194***	0.163***	0.162***	0.167***
	(0.014)	(0.014)	(0.014)	(0.014)	(0.016)	(0.016)	(0.017)	(0.017)
Some college	0.263***	0.178***	0.192***	0.196***	0.302***	0.207***	0.215***	0.222***
	(0.016)	(0.015)	(0.016)	(0.016)	(0.018)	(0.018)	(0.019)	(0.019)
Bachelor's degree	0.594***	0.398***	0.416***	0.420***	0.652***	0.445***	0.468***	0.472***
	(0.021)	(0.020)	(0.021)	(0.021)	(0.023)	(0.023)	(0.024)	(0.024)
Graduate degree	0.755***	0.521***	0.494***	0.498***	0.830***	0.547***	0.549***	0.548***
	(0.030)	(0.031)	(0.031)	(0.031)	(0.029)	(0.030)	(0.032)	(0.032)
Major industries		YES				YES		
3-digit occupations		YES				YES		
Computer *skill interactions				YES				YES
No. of Observations	9,139	9,139	8,718	8,718	10,571	10,571	9,652	9,652
R-squared	0.460	0.567	0.525	0.527	0.420	0.534	0.473	0.476

Notes: White-corrected standard errors are shown in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1. Regressions also include potential experience and its square, black, other race, Hispanic, part time worker, lives in metropolitan statistical area, veteran status, union member, female, married, female interacted with married, Census region and a constant.

Table 6. OLS pooled log hourly wage regressions (WES – years 1999, 2001, 2003)

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Computer use	0.235***	0.150***	0.090***	0.070***	0.046***	0.016***	0.067***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.004)	(0.005)	(0.009)
Computer-aided tech.		-0.018***	0.009**	-0.012***	0.012***	0.010**	0.010
		(0.006)	(0.005)	(0.005)	(0.004)	(0.004)	(0.011)
Other technologies		-0.050***	-0.023***	-0.032***	-0.016***	-0.016***	-0.008
		(0.004)	(0.003)	(0.004)	(0.003)	(0.003)	(0.009)
Knowledge				0.049***	0.057***	0.056***	0.045***
				(0.003)	(0.002)	(0.002)	(0.005)
Supervision received				-0.005	0.002	0.003	-0.013
				(0.007)	(0.005)	(0.005)	(0.009)
Guidelines				0.027***	-0.009*	-0.010**	-0.012
				(0.006)	(0.005)	(0.005)	(0.010)
Complexity				0.026***	0.007	0.008	0.025***
				(0.006)	(0.004)	(0.004)	(0.008)
Scope and Effect				0.055***	0.030***	0.031***	0.052***
				(0.007)	(0.005)	(0.005)	(0.010)
Personal Contacts				0.036***	0.047***	0.045***	0.032**
				(0.005)	(0.004)	(0.004)	(0.009)
Purpose of Contacts				0.008	0.048***	0.048***	0.033***
				(0.006)	(0.005)	(0.004)	(0.011)
Physical Demands				-0.092***	0.024***	0.030***	-0.008
				(0.010)	(0.008)	(0.008)	(0.013)
Work Environment				0.140***	0.062***	0.066***	0.063***
				(0.011)	(0.008)	(0.008)	(0.008)
High school degree	0.077***	0.060***	0.054***	0.047***	0.036***	0.031***	0.037***
	(0.006)	(0.006)	(0.005)	(0.006)	(0.005)	(0.005)	(0.005)
Some college	0.185***	0.169***	0.103***	0.102***	0.071***	0.063***	0.072***
	(0.006)	(0.006)	(0.005)	(0.006)	(0.005)	(0.005)	(0.005)
Bachelor’s degree	0.463***	0.421***	0.247***	0.263***	0.196***	0.186***	0.193***
	(0.009)	(0.008)	(0.007)	(0.008)	(0.007)	(0.007)	(0.007)
Graduate degree	0.598***	0.543***	0.339***	0.336***	0.282***	0.270***	0.279***
	(0.011)	(0.011)	(0.010)	(0.011)	(0.008)	(0.008)	(0.008)
Comp. experience						0.007***	
						(0.001)	
Comp. exp. squared						-0.0001***	
						(0.000)	
WES variables[1]		YES	YES	YES	YES	YES	YES
Major industries			YES				
4-digit occupations			YES				
Establishment FE					YES	YES	YES
Job skills				YES	YES	YES	YES
Computer *skill interactions							YES
No. of Observations	64,726	64,726	64,726	58,227	58,227	58,227	58,227
R-squared	0.396	0.425	0.564	0.513	0.469	0.474	0.471

Notes: White-corrected standard errors are shown in parentheses. Standard errors were corrected for workplace clustering, when not including establishment fixed effects. Significance levels: *** p<0.01, ** p<0.05, * p<0.1. Regressions also include education levels, potential experience and its square, part time worker, union member, female, married, female interacted with married, region, year, and a constant.

[1] WES variables include non-European background, language different at home than work, ln(establishment size), % of computer users in the establishment, and tenure and its square.

Table 7. OLS IT-Skill Interaction Effects

	CPS 1997	CPS 2003	WES
Computer*Knowledge	-0.011	-0.032*	0.010*
	(0.016)	(0.018)	(0.005)
Computer *Supervision Received	0.088**	0.113***	0.043***
	(0.031)	(0.041)	(0.010)
Computer *Guidelines	-0.020	-0.047	0.005
	(0.034)	(0.047)	(0.010)
Computer *Complexity	-0.026	-0.094**	-0.036***
	(0.029)	(0.039)	(0.009)
Computer *Scope & Effect	-0.037	0.078*	-0.033***
	(0.036)	(0.047)	(0.011)
Computer*Personal Contacts	-0.019	0.080**	0.038***
	(0.027)	(0.034)	(0.009)
Computer *Purpose of Contacts	0.053	-0.002	0.020*
	(0.035)	(0.040)	(0.012)
Computer * Physical Demands	-0.051	-0.050	0.028**
	(0.032)	(0.036)	(0.012)
Computer–aided technology *Knowledge			0.005
			(0.007)
Computer –aided technology *Supervision Received			0.007
			(0.014)
Computer –aided technology *Guidelines			0.012
			(0.013)
Computer –aided technology *Complexity			-0.009
			(0.013)
Computer –aided technology *Scope & Effect			-0.003
			(0.015)
Computer–aided technology *Personal Contacts			-0.032***
			(0.011)
Computer –aided technology *Purpose of Contacts			-0.002
			(0.013)
Computer–aided technology * Physical Demands			0.027**
			(0.013)

Table 7 Continued. OLS IT-Skill Interaction Effects

	CPS 1997	CPS 2003	WES
Other technology *Knowledge			0.004
			(0.005)
Other technology *Supervision Received			-0.034***
			(0.011)
Other technology *Guidelines			0.002
			(0.010)
Other technology *Complexity			0.006
			(0.010)
Other technology *Scope & Effect			0.006
			(0.012)
Other technology *Personal Contacts			-0.020**
			(0.009)
Other technology *Purpose of Contacts			-0.004
			(0.010)
Other technology * Physical Demands			0.021**
			(0.010)
P-value for joint significance of computer interactions	0.016	0.000	0.000
P-value for joint significance of computer-aided			0.000
P-value for joint significance of other technology			0.000
Observations	8,718	9,652	58,227

Notes: White-corrected standard errors are shown in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table 8. Returns to Adopting a Computer, by Skill Level (WES 1999–2004)

VARIABLES	(1)	(2)
Δ Computer	0.026***	0.050**
	(0.008)	(0.019)
Δ Computer *Knowledge		-0.001
		(0.012)
Δ Computer * Supervision Received		0.007
		(0.024)
Δ Computer * Guidelines		0.006
		(0.018)
Δ Computer * Complexity		-0.036
		(0.022)
Δ Computer * Scope and Effect		0.022
		(0.025)
Δ Computer *Personal Contacts		0.024
		(0.020)
Δ Computer * Purpose of Contacts		-0.021
		(0.025)
Δ Computer * Physical Demands		-0.016
		(0.024)
No. of Observations	14,697	14,697
P-value for joint significance of interaction terms		0.621
Adjusted R-squared	0.070	0.070

Notes: White-corrected standard errors are shown in parentheses. The sample is restricted to those employees who responded to the survey in both years, remained in the same establishment, and did not use a computer in the first year. Skills are for the second year of each panel. Significance levels: *** p<0.01, ** p<0.05, * p<0.1. Regressions also include education level, potential experience squared, tenure squared, home language not work language, part-time worker, married, married*female, union member, recent promotion, ln(establishment size), % of computer users in the establishment, panel indicators, changes in skills associated with changes in 3-digit occupation, establishment fixed effects, and a constant.

Table 9. Returns to Most Frequently Used Applications (WES pooled 1999, 2001, 2003)
Dependent Variable : Log(hourly wage)

VARIABLES	(1)	(2)
Word processing	0.064***	0.096***
	(0.006)	(0.014)
Spreadsheets	0.072***	0.112***
	(0.006)	(0.016)
Databases	0.023***	0.033***
	(0.006)	(0.015)
Desktop publishing	0.038**	0.074
	(0.017)	(0.048)
Management applications	0.075***	0.132***
	(0.011)	(0.029)
Communication	0.149***	0.132***
	(0.007)	(0.017)
Specialized office	0.028***	0.048***
	(0.005)	(0.012)
Graphics	0.038***	0.193***
	(0.015)	(0.043)
Data analysis	0.044***	0.054
	(0.016)	(0.042)
Programming	0.070***	0.044
	(0.014)	(0.042)
Computer-assisted design	0.034**	0.035
	(0.015)	(0.048)
Computer-assisted engineering	0.054**	-0.044
	(0.022)	(0.068)
Expert systems	0.043***	0.049*
	(0.012)	(0.029)
Other IT	0.031***	0.049***
	(0.006)	(0.015)
Job Skill	YES	YES
Establishment FE	YES	YES
Software*skill Interactions		YES
No. of Observations	58,227	58,227
P-value for joint significance of interaction terms		0.000
R-squared	0.477	0.478

Notes: White-corrected standard errors are shown in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1. Regressions also include education levels, potential experience and its square, non-European background, ln(establishment size), % of computer users in the establishment, tenure and its square, language different at home than work, part time worker, union member, female, married, female interacted with married, region, year, and a constant.

Table 10. Returns to Communications and Word Processing Applications, by Skill

Communications	0.132***
	(0.017)
Communications* Knowledge	0.008
	(0.009)
Communications* Supervision received	0.064***
	(0.020)
Communications* Guidelines	0.032*
	(0.019)
Communications *Complexity	-0.100***
	(0.017)
Communications* Scope & Effect	-0.037*
	(0.020)
Communications*Personal Contacts	0.085***
	(0.016)
Communication*Purpose of Contacts	0.049***
	(0.018)
Communication*Physical Demands	0.002
	(0.020)
Word processing	0.096***
	(0.014)
Word processing* Knowledge	0.019***
	(0.007)
Word processing* Supervision received	0.033**
	(0.016)
Word processing*Guidelines	-0.029*
	(0.016)
Word processing*Complexity	-0.055***
	(0.013)
Word processing*Scope & Effect	-0.001
	(0.017)
Word processing*Personal Contacts	0.035***
	(0.013)
Word processing*Purpose of Contacts	0.026*
	(0.015)
Word processing*Physical Demands	0.048***
	(0.016)
Observations	58,227

Notes: White-corrected tandard errors are shown in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1. Specification as in column 2 of Table 9.

Table 11. Returns to Programming Applications, by Skill

Programming	0.044
	(0.042)
Programming* Knowledge	0.005
	(0.023)
Programming* Supervision received	0.041
	(0.053)
Programming*Guidelines	0.074
	(0.066)
Programming*Complexity	-0.064
	(0.045)
Programming*Scope & Effect	-0.024
	(0.071)
Programming*Personal Contacts	-0.010
	(0.034)
Programming*Purpose of Contacts	0.032
	(0.049)
Programming*Physical Demands	-0.003
	(0.050)
Observations	58,227

Notes: Standard errors are shown in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1. Specification as in column 2 of Table 9.

Table 12. Short-term Returns to Adopting a Computer and Specific Major Applications
Dependent Variable: Log(hourly wage)

VARIABLES	(1)	(2)
ΔWord processing	0.026	0.050
	(0.018)	(0.047)
ΔSpreadsheets	0.013	0.038
	(0.023)	(0.069)
ΔDatabases	0.036*	0.140***
	(0.019)	(0.048)
ΔDesktop publishing	0.015	-0.125**
	(0.048)	(0.058)
ΔManagement applications	0.069***	0.161**
	(0.026)	(0.072)
ΔCommunication	0.010	0.055
	(0.021)	(0.044)
ΔSpecialized office	0.034**	0.052
	(0.014)	(0.040)
ΔGraphics	0.007	-0.038
	(0.045)	(0.123)
ΔData analysis	0.046	0.096
	(0.046)	(0.103)
ΔProgramming	-0.046	-0.051
	(0.052)	(0.128)
ΔComputer-assisted design	-0.008	0.065
	(0.047)	(0.147)
ΔComputer-assisted engineering	0.224***	-0.062
	(0.071)	(0.101)
ΔExpert systems	0.016	0.022
	(0.035)	(0.055)
ΔOther IT	0.020	-0.003
	(0.018)	(0.051)
ΔSkills	YES	
Applications* skill interactions		YES
P-value for joint significance of interactions		0.000
Adjusted R-squared	0.070	0.068
No. of Observations	14,697	14,697

Notes: Standard errors are shown in parentheses. Skills are measured for the second year of the panel. Significance levels: *** p<0.01, ** p<0.05, * p<0.1. Regressions also include education level, potential experience squared, computer experience squared, tenure squared, home language not work language, part-time worker, married, married*female, union member, recent promotion, ln(establishment size), % of computer users in the establishment, panel indicators, establishment fixed-effects, and a constant.

Table 13.Returns to Adopting Selected Applications, by Skill (WES 1999–2004)

Communications	0.055
	(0.044)
Communications* Knowledge	-0.005
	(0.034)
Communications* Supervision received	0.064
	(0.054)
Communications* Guidelines	-0.026
	(0.049)
Communications *Complexity	-0.019
	(0.053)
Communications* Scope & Effect	-0.014
	(0.066)
Communications*Personal Contacts	0.086*
	(0.049)
Communication*Purpose of Contacts	-0.090
	(0.058)
Management	0.161**
	(0.072)
Management* Knowledge	-0.061
	(0.043)
Management* Supervision received	-0.152
	(0.096)
Management* Guidelines	-0.134*
	(0.070)
Management *Complexity	0.111
	(0.089)
Management* Scope & Effect	0.214**
	(0.091)
Management*Personal Contacts	0.142**
	(0.070)
Management*Purpose of Contacts	-0.001
	(0.087)
Computer-assisted engineering	-0.056
	(0.101)
Computer-assisted engineering* Knowledge	0.152***
	(0.056)
Computer-assisted engineering* Supervision received	-0.124
	(0.333)
Computer-assisted engineering* Guidelines	-0.328
	(0.292)
Computer-assisted engineering *Complexity	0.560**
	(0.255)
Computer-assisted engineering* Scope & Effect	-0.040
	(0.274)
Computer-assisted engineering*Personal Contacts	-0.014
	(0.097)

Notes: White-corrected standard errors are in parentheses. Significance levels: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.