Which Job Skills Are Complementary To IT Adoption And Use?

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This Version: April 2013

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 Canada. The data on job skills are linked to workers in the 1999–2005 Canadian Workplace and Employee Survey (WES), by detailed occupation. 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. We find that workers whose jobs are more specialized, involve greater interpersonal skills, and require greater knowledge receive a wage increase from using a computer in general. Furthermore, we find interpersonal skills are complementary to numerous software applications, including e-mail use. Non-routine tasks are complementary to e-mail use and spreadsheets.

JEL: J31, O30

Key words: computer use, job skills, tasks, software, technology use

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*Disclaimer: All views expressed in this paper are those of the authors and do not necessarily reflect the views or policies of the U.S. Bureau of Labor Statistics. We thank Richard Murnane, Joseph Price, Marianne Saam, Jeremy Sandford, Jay Stewart, Leslie Stratton, and Thomas Strobel for comments and participants at the 2009 Southern Economic Association meetings, the 2010 ZEW Conference on the Economics of Information and Communication Technologies, 2012 Management and Economics of ICT Conference in Munich, and 2012 NBER Summer Institute. We thank Rob Valletta for CPS computer programs. We thank Jon Bernt for research assistance and Yves Decady at Statistics Canada for data support.

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; Dostie, Jayaraman, and Trépanier 2010) have employed various panel data and IV techniques to control for unobserved individual (and sometimes establishment) heterogeneity and 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 across broad occupation groups, educational attainment, 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 job skills these computers will complement or how long it takes to learn a particular computer skill. It may also be easier to learn a specific computer application for individuals with higher ability or education. Returns to experienced users and new users may also differ 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 1980's and 1990's computers reduced the time accountants at a bank spent on routine tasks (data transfer, data entry, and computations) and increased the time they spent on more difficult tasks (data rework, valuation, communication, and analysis). 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 (in the sense that they are programmable) and complements to non-routine abstract, manual, and interactive tasks. Abstract tasks in particular are complementary as they often draw upon the information provided by computers. Many interactive and manual tasks are currently hard to automate with existing technologies (Autor 2013). 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 occupations rather than in the occupational structure of employment. She also found that the increased prevalence of computer use within occupations is associated with 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. However, Green (2012) notes that Autor, Levy, and Murnane (2003) and Spitz-Oener (2006) make many questionable assumptions about the nature of detailed tasks in order to group them into routine and non-routine categories, which may affect their results. Green (2012) goes on to find evidence in support of Author, Levy and Murnane's findings. Autor (2013) also discusses the difficulties with defining a reasonable number of tasks from the numerous tasks collected for each occupation in these data sets.

There have also been several papers examining whether there is a return to different computer skills using indicators for software applications used 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; Goss and Phillips 2002; 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 (Heckman, Stixrud, and Urzu 2006; Borghans, ter Weel, and Weinberg 2008; Green 2012). 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 a recent data set containing detailed information on computer and IT use – the Canadian Workplace and Employee Survey (WES). An advantage of using the Canadian data over other surveys 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 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 WES using detailed occupation codes. We discuss each of these data sources below.

A. Job Skills in the NCS

The NCS is an ongoing restricted–use establishment survey collected by the U.S. Bureau of Labor Statistics in order to produce measures of pay and benefits for U.S. government workers.[2] Unlike the DOT and its successor, the Occupational Information Network (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. NCS data on job skills were first collected in 1997 by field economists who visited about 19,800 sampled establishments and randomly selected 5–20 jobs from each establishment's personnel records for a total sample of 147,601 jobs, covering about 477 3-digit occupations. The majority of establishments are in the sample on a five-year rotation, with some larger establishments included with certainty, but a new sample of establishments is introduced each year. Therefore, between 1997 and 2005, the

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

majority of the sample is new and should reflect any broad shift in skills over the period, although any differences are smoothed.[4] Detailed information about the jobs, but no demographic information about the workers holding these positions, was obtained through interviews with human resources representatives from each establishment in the initial interview, with only updates made at subsequent interviews. If the job title no longer exists in future years, then the sampled job is dropped from the sample. The unique feature of this dataset that we explore is a group of 9 "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).[5] Gittleman and Pierce (2007) find that these job content factors explain 75% of the wage variation in the survey and averages at the occupation level are highly correlated with job characteristics in DOT.

These leveling factors include: knowledge; supervision received; guidelines; complexity; scope and effect; personal contacts; purpose of contacts; physical demands; work environment.[6] All factors were originally recorded on Likert scales, ranging from 1–3 to 1–9. Because different establishments report different ratings for each factor, we calculated the employment-weighted median of each factor for each three-digit 1990 Census occupation code.[7] We then match the

[4] O*NET skills, on the other hand, are not updated frequently nor is it apparent in what year a particular occupation's skills were added (Autor 2013).
[5] Autor and Handel (2012) and Acemoglu and Autor (2011) argue that job tasks are an application of a worker's skill endowment and workers can modify their tasks as jobs change. Using the Princeton Data Improvement Initiative (PDII) Survey, Autor and Handel (2012) find evidence that job tasks differ among workers within occupations.
[6] 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 regressions.
[7] One limitation of this approach is that we cannot also capture within occupation differences in job requirements on wages. 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

occupations to those used in the WES, so that workers observed in the WES can be assigned a corresponding median skill level according to their job.[8] To maintain respondent privacy, we are only able to create a median for those occupation cells that contain at least seven job observations, working in at least 3 separate establishments, and no single establishment accounts for more than 60 percent of the weight within a cell. This decreases our WES sample size by about 10 percent. Below we provide a brief summary of what each factor measures and hypothesize 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. This is similar to our general notion of cognitive skills. 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. 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). On the other hand, a low score indicates a job that could potentially be programmed.
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

most detailed occupation categories, and that the variation is higher for managerial and professional occupations than for blue collar occupations. Using person-level data on self-occupation. Autor and Handel (2012) find that although occupation-specific skills do control for a significant amount of the variation in wages, job tasks vary within occupations by education, minority status and English language proficiency and this additional variation can also predict wages.

[8] 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.

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 provided by the supervisor. We expect 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 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). This factor is correlated with supervision received (Gibbs, Levenson, and Zoghi 2010). In Appendix Table A1, we present the Pearson correlations among the factors.
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 because a high score indicates non-routine cognitive work. A low score can be associated with how

specialized the job is as opposed to how much the worker must ‘multi-task’ on the job (Gibbs, Levenson, and Zoghi 2010).

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 because 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 desktop 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. Green (2012) was able to distinguish repetitive physical tasks among physicals tasks and found that while computer use increased in the U.K. there was no corresponding change in repetitive physical tasks even while other influence skills rose.
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. The Canadian WES and Technology Questions

The WES is a restricted-access employer-employee linked data set that was collected annually from 1999-2006.[9] 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 from an employer-provided list and followed for two years; however, in 2006, employees were not re-interviewed.[10] We only use data from 1999–2005, which thus includes three sets of two-year employee panels. The sample of employees in the first year of each panel is 23,540, 20,352, 20,834, and 24,197 respectively. The sample in the second year is about 4,000 fewer employees due to attrition. These data allow us to control for a rich set of observable individual and establishment characteristics as well as unobservables, such as a worker's ability to learn to use new technology, which may affect both computer adoption and wages. In this paper, we match 1999 NCS skills with the 1999–2000 WES, the 2001 NCS skills with the 2001–2002 WES, the 2003 NCS skills with the 2003-2004 WES, and 2005 NCS skills with the 2005 WES by detailed

[9] Our programs are run by Statistics Canada analysts.
[10] In establishments with fewer than four employees, all employees were selected.

occupation. Occupations are coded from employee responses and are thus subject to occupation inflation similar to what is found in household surveys.[11]

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). In our analysis, we use the hourly wage created by Statistics Canada, who divided the wage or salary by the appropriate frequency. Unlike in the CPS, wages are not top coded.

In addition to information on a rich set of establishment characteristics, the WES also includes detailed information about the use of computers, software applications, and other technologies used by employees. Employees are asked how intensively they use computerized devices at work and their experience using a computer in any workplace. 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, 61% of Canadian workers used a computer (Table 1). By 2005, 67% of Canadian workers were using a computer. Workers 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. These software categories include: word processing, spreadsheets, databases, desktop publishing, management applications, communications, specialized office applications, graphics and presentations, data analysis, programming languages, computer-aided

[11] Comparing occupations in the CPS to those in the Occupational Employment Statistics (OES), Abraham and Spletzer (2010) found that the CPS underreported low-skilled jobs. If this is also the case in the WES, our estimates of the returns to skills that we would expect to be highly compensated will be biased towards zero.

design, computer-aided engineering, expert systems, and other software applications. Therefore, we can determine in great detail how the computer is used to complement the worker's job. In Table 1, 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% of workers using this application. By 2005, 43% of workers were using word processing. Between 1999–2005, there was growth in the use of all of the applications, with especially high jumps in usage associated with increases in computer use from 2001–2003. In 2005, communication software applications, such as internet and email, were used by 41% of workers, spreadsheets were used by 36%, followed closely by databases (29%) and specialized office applications (32%). A much smaller proportion of workers used graphics and presentations (16%) and programming language (6%) applications. In addition, 12% used data analysis applications, 12% used management applications, and 9% used desktop publishing. In 1999, the mean number of software applications reported conditional upon computer use was 2.6. By 2005, computer users were using, on average, 3.8 different software applications.

Workers were asked separately about using computer-assisted technologies in the course of their normal duties, such as industrial robots and retail scanning systems, and other machines or technological devices used at least one hour per day, such as cash registers, sales terminals, typewriters, vehicles and industrial machinery. These other computerized technologies are more likely to substitute for routine tasks and not likely to require advanced cognitive skills for use (Zoghi and Pabilonia 2007). Indeed, using the WES, Riddell and Song (2012) found that higher education increases the probability of using a desktop computer but not these other technologies. Approximately 13% of workers used computer-assisted technologies and 26% of workers used other machines or technological devices. There was little change in the usage rates for either type of technology between 1999 and 2005.

C. Descriptive Analysis

Table 2 presents the descriptive statistics for the WES variables and linked NCS job skills used in our analyses, by general computer use status. We find many significant differences between computer users and non-users. From 1999–2005, the earnings of computer users compared to non-users rose each year, from 40% more in 1999 to 53% more in 2005. Skill requirements for the jobs held by computer users are significantly different from those for jobs held by non-users.[12] 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 1999 and 2005, computer users' scores fell slightly in knowledge, complexity, scope and effect, personal contacts, and purpose of contacts, which measure cognitive and interactive skills. This 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).[13]

Computer users and non-users are equally likely to be non-European or an immigrant in most years. From 1999–2002, users are more likely to speak the same language at work and at home than nonusers. Throughout the period (1999-2005), computer users also have greater tenure at their establishment, work in larger establishments, and work in establishments with a higher proportion of computer users than non-users. Not surprisingly, users have much higher years of computer experience than non-users. In 1999, users had on average 8.64 years of

[12] In estimates based upon the 1997 and 2003 CPS computer use supplements (not shown), we also found job skill scores for computer users and non-users in the U.S to be quite similar to those for Canadian workers.
[13] In Appendix Table A2, we document the change in the average job skill levels of Canadian workers over the period. On average, jobs became more autonomous, more specialized (as measured by complexity), more interdependent (as measured by scope), and less physically demanding.

computer experience while non-users had only 1.53 years on average. By 2005, computer users had almost 12 years of computer experience. They were also more likely to have a Bachelor's degree, 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 general computer use, we begin by estimating a standard cross-sectional Mincerian wage equation augmented by a computer use indicator, similar to Krueger (1993):

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

where W_{it} is individual *i*'s hourly wage at time *t*; X_{it} is a vector of observable individual characteristics of *i* (as well as workplace attributes to which *i* is linked in the WES in most specifications) at time *t*; $Comp_{it}$ is a binary variable indicating that individual *i* used a computer on the job 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 sets of occupation dummies.[14] Then, we replace these dummies with the job skills that these occupations require. In addition, we have a panel of establishments and three panels of employees within those establishments. Thus, when looking at the returns to computer use, we can control for establishment fixed-effects to remove time-invariant unobserved establishment-level heterogeneity. We can further estimate returns to computer adoption and control for individual-level heterogeneity.

We first pool 1999, 2001, 2003, and 2005 employee cross-sections (Table 3) to estimate equation (1).[15] In column (1) of Table 3, we present the return to computer use using 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.[16] Other control variables included are potential experience and its square (measured as age - years of schooling - 6), indicators for part-time worker, non-European background, married, female, female interacted with married, union member, region, year, and a constant. In order to measure the percentage effect of computer use on wages, it is necessary to transform the coefficients using $100*(\exp(\gamma) - 1)$. The return to computer use is 27%. In all regressions, standard errors take into account potential correlations among employees within the same establishment by clustering by establishment. In column (2), we add some variables from the WES that may help explain wage growth but are unavailable in

[14] 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.
[15] We pool cross-sectional data so that we have enough observations to also control for establishment fixed-effects in some specifications. We do not include second-year employee data to avoid attrition bias.
[16] We also ran OLS wage regressions using the 1997 and 2003 CPS computer use supplements (estimates available from the authors). Results are similar enough across datasets to justify our use of the set of U.S. job skills with the Canadian data.

the CPS. These include indicators for language spoken being different in work and home, immigrant, 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-assisted technologies, such as industrial robots or retail scanning systems, and other technological devices, such as cash registers.[17] The return on general computer use falls to 16%. The return on computer-assisted technologies is negative 3% and negative 5% on other technological devices. In column (3), we add controls for detailed occupations (3-digit) and fourteen major industries. The return on general computer use then falls to 9%. The return on computer-assisted technologies is insignificant and the return on other technological devices is negative 2%. We then replace the occupation indicators with the nine job skills from the NCS, which are linked to the WES by 3-digit occupation codes. Because not all of the occupations could be matched to job skills, the sample size is reduced by 10%. The remaining sample includes workers in 258 unique 3-digit occupations (out of 286).[18] The return to general computer use in column (4) is 7%. Therefore, these job skills control for most of the observed wage differences between occupations. Overall, including the skill indicators, we can account for 53% of the variation in wages. We note that 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. We further take advantage of the matched employer data by controlling for establishment-level fixed effects in column (5). The return to general computer use falls to 5% and the return to computer-assisted technologies is about 1%. The latter return is in contrast to findings by Entorf, Gollac, and Kramarz (1999), but consistent with recent research

[17] Coefficient estimates on general computer use are robust to the exclusion of indicators for these other computerized technologies.
[18] Means of the variables between the sample before the match and after the match are similar (see Appendix Table A3).

by Basker (2012) who found short-run gains in labor productivity for stores introducing barcode scanners in the late 1970s and early 1980s. In addition, the return to the physical demands factor changes from a negative to a positive and becomes significant, suggesting that we were previously not adequately controlling for differences in compensation between establishments. According to the theory of compensating differentials, workers should receive a wage premium for physical stress, all else equal, although previous studies have not found evidence in support of the theory. Without adequate establishment controls, we may just be capturing differences in wages attributable to predominately white-collar versus blue-collar establishments. We also find that workers with higher scores on knowledge, guidelines, scope and effect, personal contacts, purpose of contacts, and work environment also earn higher wages while workers with higher scores on supervision received and complexity earn lower wages. Note that we should be careful not to interpret these positive effects as the price of the skill in each of these categories as we do the return on earning a college degree because workers may sort into occupations based upon their whole set of skill endowments (Heckman and Acheinkman 1986; Autor and Handel 2012; Green 2012). Individual coefficients on these job skills could be biased by cross-occupation correlations between returns to job skills.

In column (6), we add years of computer experience and its square to the specification. Computers users earn slightly higher wages than non-users (1.6% more), but more experienced users earn even higher returns. The average computer user with 10 years of computer experience earns a wage premium of 7.6% over never-users. This is consistent with findings by Entorf and Kramarz (1997), Pabilonia and Zoghi (2005), and Zoghi and Pabilonia (2007). Finally, in column (7), we present estimates for returns to computer use (of average experience level) and skills when we allow the return to computer use to vary by job skill requirements. We subtract off the (NCS) population median skill value for each skill before interacting these variables as recommended in Wooldridge (2009) in order to estimate the average treatment effect.[19] We also allow the return to using other computerized technologies to vary by job skill requirements. Including job skill indicators interacted with computer usage allows us to ask both what job skills are complementary to computer use and also what are the returns to computer skills (as proxied by the technology used) at the median skill levels. The main effect for computer use is 9.4% for a worker with median level job skills. There is no main effect for other computerized technologies for a worker with median level job skills.

Table 4 presents estimates for the interaction effects for specification 7 of Table 3. Workers in jobs requiring greater than median knowledge get a small, but significant wage boost from using a computer. Contrary to our initial hypotheses, those workers whose jobs are relatively more specialized (as measured by complexity) than the median job earn higher wages when using a computer. However, workers who use computers and have more complex tasks earn more than nonusers (p-value on of the joint test of main and interaction effect is significant). 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 workers earn higher wages when using computer-assisted technologies in riskier jobs. Workers who have higher than median scores on supervision received (i.e. more autonomy on the job) earn lower wages when using other technological devices than workers who have median scores on supervision and lower wages than non-device users. Workers using computer-assisted technology and other technological devices who have higher than median skills on

[19] The skill in the interaction is the difference between the NCS occupation-specific median and the NCS full sample median because skills are measured on a Likert-type scale so the average skill is not very meaningful. The median skills were 3 for knowledge, 2 for supervision received, 2 for guidelines, 2 for complexity, 2 for scope and effect, 2 for personal contacts, 1 for purpose of contacts, 2 for physical demands, and 1 for work environment in all years, except in 2001 when physical demands was 1.

personal contacts also earn less than those who use these devices and have median skills. In Appendix Table A4, we show predicted wages for computer users with median skills compared to those with skills one above and one below the median level.

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:

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

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

in order to estimate the following first-differenced model:

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

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; δ_i is an unobserved time-invariant individual-specific effect.; $\Delta\alpha$, β,$\Delta\gamma^{m}$, γ^{a}_{t+1}, γ^{c}_{t} are parameters to be estimated; and ε_i is a stochastic disturbance term assumed to follow a normal distribution. The return to computer use varies over time for continued users when $\gamma^{m}_{t} \neq \gamma^{m}_{t+1}$.

However, we note that this model restricts the remaining coefficients to being identical in each difference. Therefore, following Zoghi and Pabilonia (2007), we restrict the WES sample to nonusers in the first year of each panel and estimate the following first-differenced model:

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

where X_{ijt} includes time-varying controls for individual *i* in establishment *j*, $Comp_{ijt}$ is equal to 1 if individual *i* adopts a computer in year *t+1*, $Year2000_{ijt}$ and $Year2002_{ijt}$ 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); E_j is a time-invariant establishment-specific effect; $\Delta\alpha$, β, γ, μ, η and λ are parameters to be estimated.[20] When estimating this specification, we include only workers who do not change establishments and thereby minimize concerns about the importance of time-varying 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 presented in Table 3, which are returns for the average computer user.

Results for equation (5) are reported in column (1) of Table 5. The return in each column is a short-run return to computer adoption conditional upon being able to adopt (i.e. not already using a desktop computer in the first year of each employee panel). The overall computer adoption rate in our sample was 16%. We include the standard controls that change over time.[21] We also include controls for changes in skills associated with the worker changing occupations within the establishment and indicators for a job change and whether the worker was promoted, which help to control for the potential endogeneity of adopting a computer as part of an internal job change. Our sample size includes 31,846 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 job skills and covered

[20] When we estimated equation (4), we found that the wage return to adopters and continuing users was about the same over a year, but there was no corresponding wage loss for those who no longer used a computer (estimates available upon request).

[21] We exclude controls for changes in the use of other computerized technologies in this specification, but examine the returns to adopting these other technologies among initial year non-users in separate specifications below.

the period 1999–2002, found a return of about 3.6% in the first year of adoption conditional upon not using a computer in the first year. In column (1), we find 2.8% higher wage growth for computer adopters. In column (2), we then allow the return to adopting a computer to vary by the job skills associated with the occupation held by the employees in the second year of the panel (again we subtract off the median skill level before creating the interaction terms). The short-run return to adopting a computer is 3% for the worker with median skill levels. Only the coefficient on the supervision received interaction effect is statistically significant. Those workers who require more supervision on the job earn a higher return to adopting a computer than those with median supervision level. In Appendix Table A5, we show predicted first-year wage growth for adopters with median skills compared to those with skills one above and one below the median level.

We repeat this analysis substituting computer adoption in equation (5) with computer-assisted technology adoption, and then alternatively other technological device adoption (Table 5, columns 3-6). In each case, we restrict the sample to employees who did not use the technology in the first year of each panel. The adoption rate for computer-assisted technologies was about 9% and the adoption rate for other technological devices was about 19%. As in Zoghi and Pabilonia (2007), we find no short-run wage premium for adopting these alternative technologies for the worker with median skills nor do we find that adoption is complementary to skill levels.

B. Returns to Software Application Use/Adoption and Skills

In this section, we take further advantage of the detailed computer use questions available 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 applications, databases, spreadsheets, communications, expert systems, management applications, graphics, programming languages, desktop publishing, data analysis, computer-aided design, computer-aided engineering, or other software applications. In all of our specifications, we also include establishment fixed-effects and controls for job skills. In column (1) of Table 6, we find considerable variation in the returns to main software application used where the comparison group is non-computer users.[22] A worker using programming language applications as their main application earns 8% more than a non-computer user. Those using communications and e-mail as their main application have 18% 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 may share in these gains (Lee and Kim 2004).

In column (2) of Table 6, we allow the return to using these applications to vary by job skills. We still find that there is a large return (24%) to using the e-mail and internet (i.e. communications) *per se* for the worker with the median skill level. In addition, we find that these communications applications are complementary to knowledge, guidelines, and personal contacts (see Table 7-8 for 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 actually enhances the productivity of workers whose jobs require greater than the median communication skills. We also find that communications applications are complementary to more specialized

[22] We similarly ran regressions using the first two most frequently used applications. Results are qualitatively similar, but smaller 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 smaller in magnitude.

jobs (as measured by complexity). The returns to word processing applications, spreadsheets, management applications, and graphics are also higher for relatively more specialized jobs (as measured by complexity) and jobs requiring greater knowledge. We find that spreadsheets, communications, specialized office, physical demands, programming, and expert systems are complementary to physical demands. Some of these latter effects are consistent with Green (2012) who found that using a computer for word processing or email is positively correlated with repetitive physical skills. We find that those who adopt programming as their main application and who receive greater supervision earn more than those who use programming applications but have the median level of supervision. It is likely that we do not find that programming applications are complementary to many job skills because less than 1% report using programming applications as their main application.

In Table 9, 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 using a first-differenced model similar to equation (5).[23] In column (1), we control for the standard controls and changes in skills. We find significant wage returns in the first-year of adopting word processing, management, and specialized office applications, but not communications applications. These applications are likely to require or complement critical thinking skills.

In column (2), we control for the interaction between 2nd year skill levels and computer applications adopted. In Tables 10-11, we present estimates for the interaction of adopting main applications and skills. There are no significant interaction effects for word processing, as we found in the cross-sectional results. However, we find that adopting spreadsheets when used as the primary computer application is complementary to specialization and interpersonal skills, as

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

measured by personal contacts. Adopting graphics and presentations applications is complementary to greater than median skill level on guidelines, i.e. fewer guidelines. Adopting programming applications is complementary to fewer guidelines and fewer interpersonal skills required in the short-run. However, estimates are also based upon small cell sizes. Adopting graphics or computer-aided engineering applications are complementary to personal contacts.

V. Conclusion

In this paper, we have examined the returns to numerous types of IT use and adoption and how those returns vary by required job skills. When controlling for a common set of nine job skills across occupations, establishment level controls, and establishment fixed effects, we still find a significant return to computer use *per se* for the average worker. 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 a job with median skill requirements, which is consistent with previous researcher's findings. The data allow us to explore the importance of skills and more detailed information on computer applications than previously available, while also controlling for unobserved establishment-level and individual-level heterogeneity. We find that Canadian workers earn a 3% short-run return to adopting a computer among current non-users with median job skill requirements while all users have a return of 9%.

Previous researchers have found that the average worker earns a return to using e-mail. 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. Workers whose jobs require them to do more interactive tasks earn higher wages if they use the internet and e-mail. In addition, knowledge and relatively more specialized jobs are complementary to both communications applications and word processing. We also find that using computer-assisted technologies, such as industrial robots and retail scanners, is complementary to knowledge.

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Table 1. Proportion Using Computers, by Application Type

	1999	2000	2001	2002	2003	2004	2005
Any computer use	0.61	0.64	0.60	0.63	0.65	0.68	0.67
Word processing	0.35	0.38	0.34	0.39	0.41	0.44	0.43
Spreadsheets	0.25	0.29	0.26	0.32	0.34	0.38	0.36
Databases	0.18	0.21	0.20	0.27	0.27	0.33	0.29
Desktop publishing	0.04	0.04	0.04	0.08	0.08	0.09	0.09
Management applications	0.05	0.07	0.06	0.11	0.12	0.14	0.12
Communications	0.19	0.27	0.23	0.34	0.37	0.44	0.41
Specialized office applications	0.21	0.23	0.24	0.29	0.32	0.32	0.32
Graphics and presentations	0.08	0.08	0.09	0.15	0.14	0.17	0.16
Data analysis	0.04	0.04	0.04	0.11	0.10	0.13	0.12
Programming languages	0.02	0.02	0.03	0.05	0.05	0.06	0.06
Computer-aided design	0.02	0.02	0.02	0.04	0.04	0.06	0.05
Computer-aided engineering	0.01	0.01	0.01	0.02	0.02	0.02	0.02
Expert systems	0.02	0.02	0.02	0.02	0.03	0.07	0.03
Other software applications	0.14	0.12	0.09	0.08	0.07	0.05	0.11
Computer-assisted technologies	0.12	0.15	0.14	0.13	0.13	0.13	0.14
Other technological devices	0.27	0.26	0.23	0.26	0.26	0.26	0.27
No. of Observations	23,540	19,364	20,352	15,669	20,834	15,814	24,197

Note: Survey weights used.

Table 2. Descriptive Statistics, by Computer Use Status

	1999		2000		2001		2002		2003		2004		2005	
	User	Non-User	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**	**24.79**	**16.21**
Job Skills														
Knowledge	**4.34**	**2.75**	**4.36**	**2.75**	**4.31**	**2.71**	**4.37**	**2.72**	**4.36**	**2.66**	**4.44**	**2.69**	**4.30**	**2.54**
Supervision Received	**2.54**	**1.92**	**2.54**	**1.93**	**2.62**	**2.04**	**2.65**	**2.04**	**2.51**	**1.91**	**2.54**	**1.93**	**2.55**	**1.92**
Guidelines	**2.23**	**1.67**	**2.23**	**1.70**	**2.19**	**1.66**	**2.22**	**1.66**	**2.25**	**1.62**	**2.29**	**1.65**	**2.23**	**1.60**
Complexity	**2.57**	**2.05**	**2.57**	**2.06**	**2.59**	**2.08**	**2.61**	**2.08**	**2.54**	**2.00**	**2.57**	**2.01**	**2.54**	**1.90**
Scope and Effect	**2.32**	**1.70**	**2.32**	**1.72**	**2.30**	**1.73**	**2.33**	**1.72**	**2.34**	**1.75**	**2.37**	**1.78**	**2.31**	**1.69**
Personal Contacts	**2.06**	**1.33**	**2.07**	**1.31**	**2.04**	**1.33**	**2.04**	**1.34**	**2.03**	**1.28**	**2.03**	**1.29**	**2.03**	**1.29**
Purpose of Contacts	**1.59**	**1.18**	**1.60**	**1.17**	**1.59**	**1.18**	**1.61**	**1.19**	**1.63**	**1.16**	**1.65**	**1.16**	**1.58**	**1.14**
Physical Demands	**1.33**	**1.86**	**1.33**	**1.88**	**1.32**	**1.87**	**1.33**	**1.86**	**1.31**	**1.89**	**1.32**	**1.89**	**1.34**	**1.88**
Work Environment	**1.22**	**1.72**	**1.23**	**1.75**	**1.23**	**1.75**	**1.23**	**1.74**	**1.23**	**1.77**	**1.24**	**1.77**	**1.25**	**1.76**
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**	**0.04**	**0.22**
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**	**0.13**	**0.23**
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**	**0.54**	**0.49**
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**	**0.19**	**0.53**
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**	**0.09**	**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	0.19	0.18
Different language work and home	**0.07**	**0.10**	**0.07**	**0.10**	**0.10**	**0.13**	**0.10**	**0.13**	0.10	0.10	0.10	0.10	0.09	0.11
Immigrant	0.17	0.18	0.17	0.17	0.20	0.19	0.20	0.19	0.19	0.19	0.18	0.18	0.17	0.19
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**	**0.16**	**0.33**
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**	**0.57**	**0.46**
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**	**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**	**9.29**	**7.64**
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**	**4.59**	**3.89**
% of computer users in establ.	**0.60**	**0.24**	**0.64**	**0.33**	**0.65**	**0.27**	**0.66**	**0.28**	**0.64**	**0.28**	**0.64**	**0.29**	**0.66**	**0.26**
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**	**11.81**	**1.75**
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**	**0.25**	**0.30**
No. of Observations	14,899	8,641	12,989	6,375	12,978	7,374	10,497	5,172	14,555	6,279	11,532	4,282	17,082	7,115

Notes: User and non-user means in bold are significantly different at the 5% level. Means and proportions are weighted to account for survey design. There are about 10% fewer observations when calculating average skills.

Table 3. OLS log hourly wage regressions (pooled 1999, 2001, 2003, 2005)

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Computer use	0.237***	0.149***	0.087***	0.070***	0.048***	0.016***	0.090***
	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.010)
Computer-assisted tech.		-0.029***	0.004	-0.003	0.009***	0.007**	-0.008
		(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.009)
Other technological dev.		-0.049***	-0.020***	-0.022***	-0.013***	-0.013***	-0.022***
		(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.007)
Knowledge				0.061***	0.062***	0.061***	0.048***
				(0.003)	(0.002)	(0.002)	(0.005)
Supervision received				-0.028***	-0.021***	-0.021***	-0.003
				(0.006)	(0.005)	(0.005)	(0.008)
Guidelines				0.047***	0.018***	0.016***	0.016**
				(0.005)	(0.004)	(0.004)	(0.008)
Complexity				-0.012**	-0.013**	-0.013***	0.002
				(0.005)	(0.005)	(0.005)	(0.007)
Scope and Effect				0.041***	0.026***	0.027***	0.024***
				(0.005)	(0.005)	(0.005)	(0.008)
Personal Contacts				0.055***	0.073***	0.071***	0.032***
				(0.005)	(0.004)	(0.004)	(0.010)
Purpose of Contacts				0.026***	0.044***	0.045***	0.050**
				(0.005)	(0.005)	(0.005)	(0.012)
Physical Demands				-0.011	0.067***	0.073***	0.055***
				(0.001)	(0.009)	(0.009)	(0.010)
Work Environment				0.087***	0.036***	0.039***	0.025**
				(0.010)	(0.009)	(0.009)	(0.012)
High school degree	0.073***	0.058***	0.049***	0.045***	0.027***	0.022***	0.028***
	(0.006)	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)
Some college	0.185***	0.170***	0.099***	0.107***	0.069***	0.060***	0.069***
	(0.006)	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)
Bachelor’s degree	0.460***	0.421***	0.241***	0.272***	0.198***	0.187***	0.195***
	(0.008)	(0.007)	(0.006)	(0.007)	(0.006)	(0.006)	(0.006)
Graduate degree	0.600***	0.551***	0.336***	0.364***	0.287***	0.272***	0.281***
	(0.010)	(0.010)	(0.009)	(0.010)	(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	YES	YES	YES	YES
3-digit occupations			YES				
Establishment FE					YES	YES	YES
Job skills				YES	YES	YES	YES
Computer *skill interactions							YES
Computer-assist tech*skill interactions							YES
Other tech*skill interactions							YES
No. of Observations	88,923	88,923	88,923	86,423	86,423	86,423	86,423
R-squared	0.398	0.433	0.575	0.533	0.657	0.659	0.658

Notes: Robust standard errors are shown in parentheses and corrected for workplace clustering. In specification 7, we subtract off the median skill level before creating the interaction terms. The interpretation of the return on each skill is partial effect for a non-computer user. 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, immigrant, ln(establishment size), % of computer users in the establishment, and job tenure and its square.

Table 4. OLS Estimates of IT-Job Skill Interactions

	General Computer Use (1)	Computer-assisted technology (2)	Other Technological Device (3)
IT	0.090***	-0.008	-0.022***
	(0.010)	(0.009)	(0.007)
IT*Knowledge	0.015**	0.010*	-0.001
	(0.005)	(0.006)	(0.005)
IT*Supervision Received	-0.014	0.000	-0.020**
	(0.010)	(0.012)	(0.010)
IT*Guidelines	0.001	-0.006	-0.004
	(0.008)	(0.010)	(0.008)
IT*Complexity	-0.030***	-0.001	0.008
	(0.009)	(0.011)	(0.009)
IT*Scope & Effect	0.006	-0.004	0.012
	(0.009)	(0.011)	(0.009)
IT*Personal Contacts	0.069***	-0.037***	-0.028***
	(0.010)	(0.010)	(0.008)
IT*Purpose of Contacts	0.003	-0.012	-0.007
	(0.013)	(0.012)	(0.011)
IT*Physical Demands	0.016***	0.003	-0.005
	(0.006)	(0.007)	(0.006)
IT*Work Environment	0.005	0.013**	0.006
	(0.010)	(0.011)	(0.010)
P-value for joint significance of IT interaction terms	0.000	0.000	0.000

Notes: These interactions are from specification 7 in Table 3. We subtract the median skill level before creating the interaction term. The first row is repeated from Table 3 and represents the main effect of IT use for an employee with median job skills. Robust standard errors are shown in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table 5. Short-run Returns to Adopting a Technology, by Skill (1999-2004)

	General Computer use		Computer-assisted Technology		Other Technological Device	
	(1)	(2)	(3)	(4)	(5)	(6)
Δ IT	0.028***	0.030	-0.000	0.001	0.002	-0.000
	(0.008)	(0.023)	(0.005)	(0.010)	(0.004)	(0.008)
Δ IT * Knowledge		0.003		-0.002		0.000
		(0.012)		(0.007)		(0.010)
Δ IT * Supervision Received		-0.043*		0.000		-0.003
		(0.025)		(0.016)		(0.012)
Δ IT * Guidelines		0.010		0.010		-0.011
		(0.022)		(0.014)		(0.010)
Δ IT * Complexity		0.023		-0.007		0.016
		(0.024)		(0.016)		(0.011)
Δ IT * Scope and Effect		0.002		0.005		0.008
		(0.024)		(0.016)		(0.011)
Δ IT * Personal Contacts		0.018		0.004		0.000
		(0.026)		(0.012)		(0.001)
Δ IT * Purpose of Contacts		0.006		0.009		-0.005
		(0.031)		(0.017)		(0.012)
Δ IT * Physical Demands		-0.012		0.004		-0.001
		(0.015)		(0.008)		(0.007)
Δ IT * Work Environment		0.012		-0.002		-0.004
		(0.027)		(0.014)		(0.012)
No. of Worker-Year Observations	31,846	31,846	86,210	86,210	75,116	75,116
P-value for joint significance of interaction terms		0.6219		0. 796		0.647
Adjusted R-squared	0.074	0.0745	0.065	0.065	0.074	0.074

Notes: 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. We subtract the sample median skill before creating the interaction term. Standard errors are corrected for clustering by establishment. 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, job change, 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 6. Returns to Most Frequently Used Applications (WES pooled 1999, 2001, 2003, 2005)
Dependent Variable : Log(hourly wage)

VARIABLES	(1)	(2)
Word processing	0.066***	0.098***
	(0.005)	(0.012)
Spreadsheets	0.067***	0.108***
	(0.006)	(0.014)
Databases	0.024***	0.051***
	(0.005)	(0.013)
Desktop publishing	0.038***	0.077**
	(0.014)	(0.036)
Management applications	0.071***	0.130***
	(0.001)	(0.024)
Communications	0.161***	0.215***
	(0.006)	(0.017)
Specialized office applications	0.028***	0.054***
	(0.005)	(0.011)
Graphics and presentations	0.025**	0.134***
	(0.013)	(0.030)
Data analysis	0.041***	0.089***
	(0.013)	(0.031)
Programming languages	0.079***	0.154***
	(0.011)	(0.031)
Computer-aided design	0.046***	0.128**
	(0.013)	(0.050)
Computer-aided engineering	0.059***	0.096
	(0.018)	(0.067)
Expert systems	0.032***	0.073***
	(0.001)	(0.024)
Other software applications	0.030***	0.082***
	(0.005)	(0.013)
Job Skill	YES	YES
Establishment FE	YES	YES
Software*skill interactions		YES
No. of Observations	86,423	86,423
P-value for joint significance of interaction terms		0.000
Adjusted R-squared	0.661	0.663

Notes: Robust standard errors are shown in parentheses and corrected for workplace clustering. We subtract the sample median skill before creating the interaction term. Significance levels: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Regressions also include education levels, potential experience and its square, non-European background, immigrant, ln(establishment size), % of computer users in the establishment, tenure and its square, language different at home than work, immigrant, part time worker, computer – assisted technology, other technological device, union member, female, married, female interacted with married, region, year, and a constant.

Table 7. OLS Estimates of Main Computer Application-Job Skill Interactions

	Word Processing (1)	Spreadsheets (2)	Databases (3)	Desktop Publishing (4)	Management Applications (5)	Communications (6)	Specialized Office (7)
Application	0.098***	0.108***	0.051***	0.077**	0.130***	0.215***	0.054***
	(0.012)	(0.014)	(0.013)	(0.036)	(0.024)	(0.017)	(0.011)
Application*Knowledge	0.023***	0.020**	0.009	-0.012	0.035**	0.017*	0.007
	(0.007)	(0.009)	(0.008)	(0.023)	(0.018)	(0.009)	(0.006)
Application*Supervision	-0.000	-0.018	-0.006	0.100*	-0.055	-0.023	-0.017
	(0.016)	(0.022)	(0.019)	(0.054)	(0.042)	(0.021)	(0.014)
Application *Guidelines	-0.023	0.029*	-0.009	0.025	0.045	0.037*	-0.015
	(0.015)	(0.016)	(0.015)	(0.056)	(0.037)	(0.019)	(0.011)
Application *Complexity	-0.048***	-0.065***	-0.030*	-0.033	-0.073*	-0.095***	0.009
	(0.016)	(0.022)	(0.017)	(0.047)	(0.040)	(0.020)	(0.012)
Application*Scope & Effect	0.022	-0.007	0.001	-0.029	-0.003	0.018	-0.008
	(0.016)	(0.017)	(0.016)	(0.060)	(0.041)	(0.021)	(0.012)
Application *Personal Contacts	0.059***	0.088***	0.029*	0.047	0.100***	0.115***	0.051***
	(0.013)	(0.015)	(0.015)	(0.034)	(0.028)	(0.015)	(0.012)
Application *Purpose of Contacts	-0.009	0.008	0.027	-0.046	-0.019	0.021	0.003
	(0.017)	(0.020)	(0.019)	(0.056)	(0.034)	(0.019)	(0.015)
Application *Physical Demands	0.012	0.024**	0.013	0.003	0.031	0.035***	0.013*
	(0.009)	(0.011)	(0.010)	(0.035)	(0.021)	(0.013)	(0.007)
Application *Work Environment	0.001	0.020	0.005	0.030	0.014	-0.036*	0.021
	(0.017)	(0.020)	(0.018)	(0.054)	(0.037)	(0.021)	(0.014)

Notes: Standard errors are shown in parentheses and corrected for workplace clustering. We subtract the sample median skill before creating the interaction term. The first row is repeated from Table 6, column (2) and represents the main effect of the application for an employee with median job skills. Significance levels: *** p<0.01, ** p<0.05, * p<0.1. Specification as in column 2 of Table 6.

Table 8. OLS Estimates of Main Computer Application-Job Skill Interactions [CONTINUED]

	Graphics and Presentations (1)	Data Analysis (2)	Programming (3)	Computer-aided Design (4)	Computer-aided engineering (5)	Expert Systems (6)	Other Software Applications (7)
Application	0.100***	0.089***	0.154***	0.128***	0.096	0.073***	0.082***
	(0.017)	(0.031)	(0.031)	(0.050)	(0.067)	(0.024)	(0.013)
Application*Knowledge	-0.049**	0.019	-0.022	0.020	-0.007	0.020	0.025**
	(0.008)	(0.022)	(0.018)	(0.020)	(0.026)	(0.016)	(0.008)
Application*Supervision	-0.035	-0.007	-0.110**	0.004	-0.027	0.064	-0.006
	(0.045)	(0.048)	(0.046)	(0.052)	(0.056)	(0.050)	(0.018)
Application *Guidelines	-0.014	0.060	0.056	0.057	-0.012	-0.019	-0.010
	(0.038)	(0.043)	(0.042)	(0.043)	(0.058)	(0.025)	(0.014)
Application *Complexity	0.093**	-0.046	0.073	-0.044	0.011	-0.054	-0.020
	(0.040)	(0.049)	(0.054)	(0.050)	(0.060)	(0.045)	(0.017)
Application*Scope & Effect	0.019	-0.031	0.035	-0.047	0.074	-0.021	0.006
	(0.040)	(0.045)	(0.046)	(0.042)	(0.062)	(0.030)	(0.016)
Application *Personal Contacts	0.051	0.091***	-0.005	0.009	-0.022	0.083***	0.048***
	(0.037)	(0.035)	(0.034)	(0.031)	(0.047)	(0.029)	(0.015)
Application *Purpose of Contacts	0.014	-0.046	0.028	-0.057	-0.017	-0.038	-0.047***
	(0.046)	(0.042)	(0.044)	(0.038)	(0.047)	(0.033)	(0.019)
Application *Physical Demands	0.34	-0.013	0.041*	0.032	-0.039	0.041**	0.027**
	(0.024)	(0.029)	(0.024)	(0.030)	(0.039)	(0.020)	(0.011)
Application *Work Environment	-0.111**	0.012	-0.152***	-0.032	-0.077	0.031	-0.008
	(0.047)	(0.049)	(0.044)	(0.048)	(0.067)	(0.032)	(0.018)

Notes: Standard errors are shown in parentheses and corrected for workplace clustering. We subtract the sample median skill before creating the interaction term. The first row is repeated from Table 6, column (2) and represents the main effect of the application for an employee with median job skills. Significance levels: *** p<0.01, ** p<0.05, * p<0.1. Specification as in column 2 of Table 6.

Table 9. Short-term Returns to Adopting a Computer and Specific Major Applications (1999-2004)
Dependent Variable: Log(hourly wage)

VARIABLES	(1)	(2)
ΔWord processing	0.051**	0.017
	(0.022)	(0.073)
ΔSpreadsheets	0.005	0.032
	(0.025)	(0.078)
ΔDatabases	0.030	0.066
	(0.021)	(0.058)
ΔDesktop publishing	0.045	-0.204
	(0.054)	(0.154)
ΔManagement applications	0.061**	0.083
	(0.028)	(0.086)
ΔCommunications	0.023	0.051
	(0.023)	(0.051)
ΔSpecialized office applications	0.029*	0.042
	(0.016)	(0.045)
ΔGraphics and presentations	0.028	0.035
	(0.053)	(0.167)
ΔData analysis	0.057	0.040
	(0.044)	(0.093)
ΔProgramming languages	-0.062	0.430
	(0.052)	(0.297)
ΔComputer-aided design	-0.042	-0.047
	(0.043)	(0.111)
ΔComputer-aided engineering	0.127	0.795*
	(0.078)	(0.435)
ΔExpert systems	0.046	-0.010
	(0.041)	(0.100)
ΔOther software applications	0.020	-0.043
	(0.019)	(0.058)
ΔSkills	YES	YES
Applications* skill interactions		YES
P-value for joint significance of interactions		0.000
Adjusted R-squared	0.074	00742
No. of Worker-Year Observations	31,846	31,846

Notes: Robust standard errors are shown in parentheses. Skills are measured for the second year of the panel. We subtract the sample median skill before creating the interaction term. 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, job change, ln(establishment size), % of computer users in the establishment, panel indicators, establishment fixed-effects, and a constant.

Table 10. Short-term Returns to Adopting a Computer and Primary Computer Application, by Skill

	Word Processing (1)	Spreadsheets (2)	Databases (3)	Desktop Publishing (4)	Management Applications (5)	Communications (6)	Specialized Office (7)
∆Application	0.017	0.032	0.066	-0.204	0.083	0.051	0.042
	(0.073)	(0.078)	(0.058)	(0.154)	(0.086)	(0.051)	(0.045)
∆Application*Knowledge	-0.017	0.015	-0.030	0.072	-0.070	0.012	-0.008
	(0.035)	(0.045)	(0.033)	(0.055)	(0.053)	(0.041)	(0.025)
∆Application*Supervision	0.022	-0.010	-0.059	-0.280***	-0.009	0.151	-0.103*
	(0.055)	(0.060)	(0.055)	(0.100)	(0.093)	(0.107)	(0.057)
∆Application *Guidelines	-0.022	0.078	0.034	0.167	-0.033	0.055	0.019
	(0.067)	(0.065)	(0.046)	(0.146)	(0.059)	(0.073)	(0.041)
∆Application *Complexity	0.015	-0.124*	-0.001	0.332*	0.044	-0.182	0.063
	(0.053)	(0.064)	(0.061)	(0.175)	(0.115)	(0.115)	(0.057)
∆Application*Scope & Effect	0.011	0.067	0.029	-0.257*	0.068	-0.048	0.023
	(0.079)	(0.071)	(0.062)	(0.152)	(0.069)	(0.079)	(0.048)
∆Application *Personal Contacts	0.025	-0.215*	0.116	-0.164***	0.118	0.075	0.031
	(0.063)	(0.111)	(0.071)	(0.061)	(0.078)	(0.057)	(0.050)
∆Application *Purpose of Contacts	0.043	0.100	-0.009	-0.099	0.016	-0.070	0.024
	(0.096)	(0.108)	(0.081)	(0.103)	(0.109)	(0.080)	(0.062)
∆Application *Physical Demands	-0.049	0.039	-0.029	-0.134*	-0.027	-0.052	0.014
	(0.038)	(0.50)	(0.038)	(0.074)	(0.055)	(0.042)	(0.033)
∆Application *Work Environment	0.019	-0.192*	0.074	0.135	0.045	0.071	-0.001
	(0.076)	(0.117)	(0.080)	(0.141)	(0.96)	(0.056)	(0.057)

Notes: Standard errors are shown in parentheses and corrected for workplace clustering. We subtract the sample median skill before creating the interaction term. The first row is repeated from Table 9, column (2) and represents the main effect of the application for an employee with median job skills. Significance levels: *** p<0.01, ** p<0.05, * p<0.1. Specification as in column 2 of Table 9.

Table 11. Short-term Returns to Adopting a Computer and Primary Computer Application, by Skill [CONTINUED]

	Graphics and Presentations (1)	Data Analysis (2)	Programming (3)	Computer-aided Design (4)	Computer-aided engineering (5)	Expert Systems (6)	Other Software Applications (7)
∆Application	0.035	0.040	0.40	-0.047	0.795*	-0.010	-0.043
	(0.167)	(0.093)	(0.297)	(0.111)	(0.435)	(0.100)	(0.058)
∆Application*Knowledge	-0.084	0.046	0.104	0.157**	-0.224	0.029	0.008
	(0.083)	(0.050)	(0.072)	(0.074)	(0.269)	(0.042)	(0.029)
∆Application*Supervision	-0.151	0.495*	-0.073	-0.113	-0.147	0.186	-0.116
	(0.183)	(0.265)	(0.112)	(0.153)	(0.184)	(0.142)	(0.071)
∆Application *Guidelines	0.153	-0.225*	0.445***	0.353*	0.458	-0.113	-0.063
	(0.269)	(0.134)	(0.0124)	(0.182)	(0.333)	(0.088)	(0.068)
∆Application *Complexity	0.146	Omitted	0.195	Omitted	-0.036	0.008	0.139**
	(0.169)		(0.186)		(0.153)	(0.106)	(0.057)
∆Application*Scope & Effect	-0.225	-0.070	-0.666***	-0.444**	Omitted	-0.022	-0.001
	(0.305)	(0.088)	(0.121)	(0.188)		(0.130)	(0.071)
∆Application *Personal Contacts	0.300**	0.042	0.526*	0.224**	0.499*	-0.223	0.004
	(0.136)	(0.097)	(0.302)	(0.110)	(0.289)	(0.131)	(0.093)
∆Application *Purpose of Contacts	0.150	-0.331***	-0.701**	-0.218**	-0.740**	-0.032	0.048
	(0.183)	(0.116)	(0.343)	(0.090)	(0.336)	(0.111)	(0.093)
∆Application *Physical Demands	0.014	-0.145***	-0.039	0.284***	0.026	-0.005	-0.005
	(0.109)	(0.045)	(0.096)	(0.097)	(0.232)	(0.085)	(0.040)
∆Application *Work Environment	0.207	0.014	0.107	0.209	-0.242	-0.151	0.050
	(0.229)	(0.122)	(0.151)	(0.167)	(0.258)	(0.141)	(0.064)

Notes: Standard errors are shown in parentheses and corrected for workplace clustering. We subtract the sample median skill before creating the interaction term. The first row is repeated from Table 9, column (2) and represents the main effect of the application for an employee with median job skills. Significance levels: *** p<0.01, ** p<0.05, * p<0.1. Specification as in column 2 of Table 9.

Appendix

Table A1. Correlations Among Factors

Variable	1	2	3	4	5	6	7	8
1. Knowledge								
2. Supervision	0.834							
3. Guidelines	0.762	0.809						
4. Complexity	0.809	0.906	0.808					
5. Scope and Effect	0.778	0.834	0.911	0.837				
6. Personal Contacts	0.742	0.583	0.521	0.515	0.516			
7. Purpose of Contacts	0.840	0.674	0.550	0.627	0.555	0.715		
8. Physical Demands	-0.545	-0.343	-0.283	-0.286	-0.238	-0.724	-0.497	
9. Work Environment	-0.480	-0.299	-0.190	-0.207	-0.175	-0.714	-0.475	0.900

Table A2. Mean worker occupation-specific skill scores in WES

	1999	2005
Knowledge	3.72	3.73
Supervision	**2.29**	**2.35**
Guidelines	2.01	2.03
Complexity	**2.37**	**2.34**
Scope	**2.07**	**2.11**
Personal Contacts	1.78	1.77
Purpose of Contacts	1.43	1.44
Physical Demands	**1.54**	**1.51**
Work Environment	1.42	1.42
N	22,831	23,595

Note: Means in bold are statistically significantly different at the 10% level.

Table A3. Means in WES Sample versus Sample with Matching Job Skills Used in Analysis

	WES Sample	Job Skills Match Sample
Hourly wage	20.18	20.10
Education Level		
Less than High School	0.11	0.11
High School Degree	0.17	0.17
Some College	0.53	0.53
Bachelor's degree	0.13	0.13
Graduate degree	0.06	0.06
Non-European	0.17	0.17
Different language work and	0.10	0.10
Immigrant	0.18	0.18
Part-time	0.22	0.22
Married	0.54	0.54
Female	0.52	0.52
Tenure	8.43	8.41
Ln(establishment size)	4.28	4.26
% of computer users in	0.50	0.50
Yrs. of computer experience	7.16	7.18
Computer use	0.64	0.64
Computer-assisted tech.	0.13	0.13
Other technological dev.	0.26	0.26
Union member	0.27	0.26
Number of Observations	88,923	86,423

Table A4. Predicted Log Wages, by Skill Level

	Non-computer user, median	Computer User, median skills
	2.853	2.944
	User, 1<median skill	User, 1>median skill
Knowledge	2.881	3.006
Supervision Received	2.961	2.926
Guidelines	2.927	2.960
Complexity	2.971	2.916
Scope and Effect	2.914	2.973
Personal Contacts	2.843	3.044
Purpose of Contacts	NA	2.996
Physical Demands	2.873	3.014
Work Environment	NA	2.974

Note: NA stands for not applicable because the median skill is the lowest possible value of the skill.

Table A5. Predicted Wage Growth, by Skill Level

	Non-user, median skills	Adopter, median skill
	0.0223	0.0525
	Adopter, 1<median skill	Adopter, 1>median skill
Knowledge	-0.0434	-0.0002
Supervision Received	0.0067	-0.0458
Guidelines	-0.0659	0.0223
Complexity	-0.0493	0.0030
Scope and Effect	0.0067	-0.0502
Personal Contacts	0.0176	-0.0588
Purpose of Contacts	NA	0.0057
Physical Demands	0.0672	-0.1107
Work Environment	NA	0.0550

Note: NA stands for not applicable because the median skill is the lowest possible value of the skill.