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The Role of Education in Technology Use and Adoption:
Evidence from the Canadian Workplace and Employee Survey*

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Abstract

Adoption of innovations by firms and workers is an important part of the process of technological change. Many prior studies find that highly educated workers tend to adopt new technologies faster than those with less education. Such positive correlations between the level of education and the rate of technology adoption, however, do not necessarily reflect the true causal effect of education on technology adoption. Relying on data from the Workplace and Employee Survey, this study assesses the causal effects of education on technology use and adoption by using instrumental variables for schooling derived from Canadian compulsory school attendance laws. We find that education increases the probability of using computers in the job and that employees with more education have longer work experiences in using computers than those with less education. However, education does not influence the use of computer-controlled and computer-assisted devices or other technological devices such as cash registers and sales terminals. Our estimates are consistent with the view that formal education increases the use of technologies that require or enable workers to carry out higher order tasks, but not those that routinize workplace tasks.

JEL Classification: *I20, O33*

Key words: *Technology use and adoption, education, causal effects, compulsory schooling laws, heterogeneity in technology*

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Executive Summary

The creation and diffusion of new and more advanced knowledge and technologies has long been recognized as a major contributor to productivity and economic growth. As developed countries shift more toward economic activities that are knowledge-based, information, technology, and learning play an increasingly important role. The adoption of new technologies by firms and workers constitutes an important part of the process of technological diffusion and advancement. Thus, investigation of employer and employee characteristics that influence decisions to adopt new technologies is an important area of research.

Relying on data from the Canadian Workplace and Employee Survey (WES) (1999-2005), this study assesses the causal effects of workers' educational attainment on their use and adoption of new technologies. A key methodological challenge to our research is that the positive correlations between education and technology use and adoption that we expect to observe are likely to be confounded by the endogeneity of education, and thus do not necessarily reflect the true causal effects of education. In particular, positive associations between education and technology use and adoption could arise because of unobserved factors that are correlated with both variables. For example, individuals with higher innate ability and stronger motivation may be more likely to be early adopters of new technologies at the workplace and also more likely to acquire more schooling. In these circumstances standard regression methods, such as ordinary least squares (OLS) estimation, yield biased estimates of the true causal link between education and technology use and adoption.

To overcome the endogeneity of education problem, we make use of historical changes in compulsory schooling laws in Canada to create instrumental variables for assessing the causal effects of education on technology use and adoption. Moreover, we partially control for the unobserved ability of individual workers by controlling for the average observed skills of coworkers in the same firm and same occupation in our empirical analyses, which is possible due to the linked employer-employee feature of WES.

We find that employees with more education are more likely to use computers on the job. Graduating from high school increases the probability of using a computer in the workplace by 37 percentage points and an additional year of schooling increases such probability by 7 percentage points, impacts that are large in size and statistically significant. We also find that employees with more education possess longer work experiences in using a computer. Specifically, graduating from high school increases computer use experience by 6.2 years and an additional year of schooling increases computer use experience by 1.2 years. Employees with more education are not only more likely to use

computers on the job at a point in time, but also start to use computers earlier in their working lives.

The impact of education on technology use in the workplace, however, differs by the type of technology. Our IV estimates indicate that education does not exert causal effects on the use of computer-controlled and computer-assisted devices or other technological devices such as cash registers and sales terminals. In the context of the current “information and communication technology” era, these results are consistent with the view that education increases the use of technologies that require or enable workers to carry out higher order tasks, whereas schooling does not affect the use of technologies that routinize workplace tasks. Our finding is also consistent with findings from previous studies that technology is heterogeneous.

We also find evidence of heterogeneity in the impacts of education on computer use and computer use experience in the workplace. Impacts of additional schooling are largest in the range of 9 to 13 years of schooling, and somewhat lower above 13 years. The presence of heterogeneous effects helps to reconcile differences between OLS and IV estimates.

Overall, our results provide empirical support for the hypothesis that there exists a causal link between education and certain measures of technology use and adoption. Findings from this study not only shed light on the role of education in technology use and adoption, but also contribute to the literature on the non-market impacts of education. To the extent that education increases the probability of technology use and adoption, the private and social benefits of education may be understated by standard outcome measures (e.g., individual earnings). This will especially be the case if an individual employee’s education and the associated technology use also influence employer and coworker outcomes. In contrast, studies of the non-market effects of education often focus on outcomes such as health and longevity, impacts that are experienced by the individual receiving the education.

Further, this study contributes to the literature on the relationship between education and economic growth by providing empirical evidence that supports education as an effective means to enhance technology adoption and diffusion and hence technological advancement and productivity growth. It thus illuminates one specific channel through which education may enhance economic growth.

1 Introduction

The creation and diffusion of new and more advanced knowledge and technologies has long been recognized as a major contributor to productivity and economic growth. As developed countries shift more toward economic activities that are knowledge-based, information, technology, and learning play an increasingly important role. The adoption of new technologies by firms and workers constitutes an important part of the process of technological diffusion and advancement. Thus, investigation of employer and employee characteristics that influence decisions to adopt new technologies is an important area of research. The purpose of this study is to assess the causal effects of workers' educational attainment on their use and adoption of new technologies, using an employer-employee linked dataset, the Canadian Workplace and Employee Survey (WES).

A large body of prior research has shown that highly educated workers tend to adopt new technologies faster than those with less education (Welch, 1970; Wozniak, 1984, 1987; Krueger, 1993; Lleras-Muney and Lichtenberg, 2002). Generally, a new technology is associated with uncertain returns and up-front costs of adoption. How quickly producers and employees can adapt to a changing set of production possibilities partly depends on their human capital and their knowledge of the new technology. Wozniak (1987) concludes that education and information reduce adoption costs and uncertainty, and thereby raise the probability of early adoption. Krueger (1993) finds that more highly educated workers were more likely to use computers on the job in the 1980s, a period of rapid growth in the adoption of computers in the workplace.

Technology adoption can also be viewed as a reallocation decision made in response to changing economic circumstances, allowing consumers and producers to take advantage of the opportunities provided by the introduction of innovative inputs. Since the development of the concept of human capital in the 1960s, scholars have argued that highly educated workers have a comparative advantage in dealing with economic change and in implementing new technology (Shultz, 1964, 1975; Nelson and Phelps, 1966; Welch, 1970, 1973; Khaldi, 1975; Wozniak, 1984; Bartel and Lichtenberg, 1987). For example, Wozniak (1984) found that farm operators with more education are more likely to be adopters of innovations than operators with less education, although education did not affect the utilization of an innovative input several periods after its introduction.

The positive correlations between the level of education and technology use and adoption found in previous studies, however, are likely to be confounded by the endogeneity of education, and thus do not necessarily reflect the true causal effects of education on technology use and adoption. In particular, positive associations between education and technology use and adoption could arise because of unobserved factors that are correlated with both variables. For example, individuals with higher innate ability and stronger motivation may be more likely to be early adopters of new technologies at the workplace and also more likely to acquire more schooling. Therefore, positive correlations between education and technology use and adoption based on ordinary least squares (OLS) estimates may overestimate the effects of education on technology use and adoption and fail to reveal the true causal link between the two.[1]

To our knowledge, no prior research has established a causal link between education and technology use or adoption. To overcome the endogeneity of education problem, we make use of historical changes in compulsory schooling laws in Canada to create instrumental variables for education, which allows us to draw causal inferences about the effects of education on technology use and adoption. Moreover, we partially control for the unobserved ability of individual workers by controlling for the average observed skills of coworkers in the same firm and same occupation in our empirical analyses, which is possible due to the linked employer-employee feature of WES.

In addition, our study extends previous research in this area by making use of the rich information provided by WES data. As a joint decision made by workers and their firm, technology use and adoption is affected by the characteristics of both the workplace and the workers. However, due to data limitations, most previous studies on the determinants of technology adoption focus on either employer characteristics or employee characteristics, but not both (Hannan and McDowell, 1984; Levin, Levin, and Meisel, 1987; Stoneman and Kwon, 1996).[2] WES, an employer-employee linked dataset,

[1] Card (1999, 2001) and Griliches (1977) discuss the endogeneity of education and the potential biases of OLS estimates in the context of estimating the return to schooling.

[2] Hannan and McDowell (1984) examine the determinants of adoption of automatic teller machines by banks and find that larger banks and banks operating in more concentrated local banking markets register a higher conditional probability of adopting automatic teller machines.

Levin, Levin, and Meisel (1987) investigate the role of market structure in the time path of adoptions of a new technology (optical scanners) in the U.S. food store industry. They find that during the early stage enables us to take into account the characteristics of both employers and employees that may affect technology use and adoption. Another key advantage of WES is the rich information it contains on technology use and recent adoptions of new technology, which enables us to analyze a variety of measures of technology use and adoption. We are thus able to gain more insights into the role of education because the way that education affects technology adoption and use may depend on the type of technology, as found by Dunne and Troske (2005).

The WES survey provides information on two principal types of technology use in the workplace. The first group of questions relates to computer use, and asks workers whether they use a computer on the job and asks about their accumulated experience in computer use in the workplace. This type of activity is often associated with "knowledge workers" since computers allow workers to carry out a wide variety of higher order tasks and productive activities. The second set of questions relates to the use of computer-controlled and computer-assisted technologies such as retail scanning devices and industrial robots, as well as technological devices such as cash registers, sales terminals and industrial machinery. These types of technology use are less likely to be associated with knowledge workers, and are more likely to involve routine tasks. An interesting question is whether the role played by educational attainment differs between these two forms of technology use in the workplace.

Based on WES data for the period 1999-2005, we find that education increases the probability of using computers on the job. We also find that employees with more education possess longer work experiences in using computers than those with less education. However, the instrumental variable (IV) estimates indicate that education does not exert causal effects on the use of computer-controlled or computer-assisted technology, or the use of technological devices. The OLS estimates, in contrast, suggest a small positive impact. Thus, for some measures of technology use and adoption, OLS estimates are misleading in suggesting effects that are not causal, whereas in the case of

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leading firms with larger store size who are not members of chains and who operate in less concentrated markets with higher incomes and wage rates tend to adopt the scanners sooner.
Stoneman and Kwon (1996) examine the relationship between firm profitability and technology adoption. They find that non-adopters experience reduced profits as other firms adopt new technologies and that the gross profit gains to adopters of new technology are related to firm and industry characteristics, the number of other users of new technologies, and the cost of acquisition.

computer use the positive partial correlations estimated by OLS do reflect an underlying causal relationship. Overall, our results provide empirical support for the hypothesis that there exists a causal link between education and certain measures of technology use and adoption, and that one needs to be careful in drawing conclusions about causal impacts based on OLS estimates.

Findings from this study not only shed light on the role of education in technology use and adoption, but also contribute to the literature on the non-market impacts of education (Grossman, 2006; Oreopoulos and Salvanes, 2011). To the extent that education increases the probability of technology use and adoption, the private and social benefits of education may be understated by standard outcome measures (e.g., individual earnings). This will especially be the case if an individual employee's education and the associated technology use also influence employer and coworker outcomes.[3] In contrast, studies of the non-market effects of education often focus on outcomes such as health and longevity, impacts that are experienced by the individual receiving the education.

Further, this study contributes to the literature on the relationship between education and economic growth. Following work by Barro (1991, 1997) and Mankiw, Romer, and Weil (1992), a large literature based on cross-country growth regressions finds positive associations between quantity of schooling and economic growth (see Topel (1999), Krueger and Lindahl (2001), and Pritchett (2006) for extensive literature reviews). Hanushek and Woessmann (2009) further provide evidence of a causal link between cognitive skills/quality of schooling and economic growth. Our study extends this line of research by providing empirical evidence that supports education as an effective means to enhance technology adoption and diffusion and hence technological advancement and productivity growth. It thus illuminates one specific channel through which education may enhance economic growth.[4]

The remainder of the paper is organized as follows. We describe the WES data in Section 2, and explain the empirical framework used in our data analyses in Section 3. In

[3] Moretti (2004) examines human capital externalities in U.S. manufacturing and estimates that human capital externalities are responsible for an average of 0.1 percent increase in output per year during the 1980's.

[4] There are various mechanisms through which education may affect economic growth. The mechanism in our study is close to that in Nelson and Phelps (1966), Welch (1970), and Benhabib and Spiegel (2005), who argue that education may facilitate the diffusion and transmission of knowledge needed for the implementation of new technologies.

Sections 4 and 5, we report and discuss empirical results about the effects of education on alternative measures of technology use and adoption. Section 6 concludes the paper.

2 Data

2.1 The Workplace and Employee Survey

The data used in this study include all panels of the annual Canadian Workplace and Employee Survey (WES) from 1999 to 2005. WES is designed to explore a broad range of issues relating to employers and their employees. Employers and employees are linked at the micro data level; employees are selected from within sampled workplaces.

The target population of employers for WES is defined as all business locations operating in Canada that have paid employees in March of the survey year.[5] WES draws its sample from the Business Register, a list of all businesses in Canada, and thus provides a representative sample of Canadian employers. The initial sample of 6,322 workplaces selected in 1999 is followed over time and supplemented at two-year intervals with a sample of births selected from units added to the Business Register since the last survey. For the 2005 survey, the sample size of employers is 6,693.

The employee data and the workplace data are collected separately. The frame of the employee component of WES is based on lists of employees made available by the selected workplaces. A maximum of 24 employees are sampled from each workplace. In workplaces with fewer than four employees, all employees are selected. Employees are followed for two years. Fresh samples of employees are drawn on every other survey occasion (i.e., first, third, fifth, and seventh). Therefore, data at the employee level are two-year panels while the data at the workplace level constitute a seven-year panel from 1999 to 2005. The sample size of employees is 23,540 in 1999 and 24,197 in 2005.

2.2 Measures of Technology Use and Adoption

Four types of data are available in WES on technology use and adoption at the employee level: use of computer; use of computer-controlled or computer-assisted technology; use of other machine or technical device; and change in technological complexity. Our study focuses on technology use and adoption at the employee level, which is captured by four measures. These measures and the relevant survey questions are listed below.

[5] There are a few exceptions: employers in 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.

- *Computer use in the job*: Do you use a computer in your job? Please exclude sales terminal, scanners, machine monitors, etc. By a computer we mean a microcomputer, mini-computer, personal computer, mainframe computer or laptop that can be programmed to perform a variety of operations.
- *Computer use experience*: Considering all jobs you have held, how many years have you used a computer in a work environment?
- *Use of computer-controlled or computer-assisted technology*: Do you use a computer-controlled or computer-assisted technology in the course of your normal duties? For example, industrial robots, retail scanning systems, etc.
- *Use of technological device*: Do you use any other machine or technological device for at least one hour a day in the course of your normal duties? This question is meant to be inclusive and would include, for example, cash registers, sales terminals, typewriters, vehicles and industrial machinery. Do not include the car that you drive for work unless it requires a special permit.

2.3 Educational Attainment and Compulsory Schooling Laws in Canada

"Educational attainment" is a key variable in our empirical analyses. In the WES survey, employees who are surveyed for the first time, i.e., in odd survey years, are first asked about the highest grade of elementary or high school (secondary school) that they have completed. Employees are then asked whether they graduated from high school (secondary school) and whether they have received any additional education. Conditional on having received post-secondary education, respondents are asked to report the type of the additional education received.[6] We assign to each employee a total number of years of schooling based on the number of years of elementary and secondary schooling completed and the normal duration of any post-secondary education.

[6] This may include trade or vocational diploma or certificate; some college, CEGEP (post-secondary education institutions exclusive to the province of Quebec), institute of technology or nursing school; completed college, CEGEP, institute of technology or nursing school; some university; teachers' college; university certificate or diploma below the bachelor level; bachelor or undergraduate degree or teachers' college (e.g. B.A., B.Sc., B.A.Sc., or four-year B.Ed.); university certificate or diploma above the bachelor level; Master's degree (M.A., M.Sc., M.Ed., MBA, MPA or equivalent); earned doctorate; degree in medicine, dentistry, veterinary medicine, law, optometry or theology (M.D., D.D.S., D.M.D., D.V.M., LL.B., O.D., or M.DIV.) or one-year B.Ed. after another bachelor's degree; industry certified training or certification courses; or other.

Because each sample of employees is followed for two consecutive years, in even-year surveys WES only asks about any additional education obtained during the past 12 months. Conditional on having received additional education during the past 12 months, WES further asks about the type of education received using the same categories of education as in the odd-year surveys. Because such additional education is likely to be part-time, we assign 0.5 years of education rather than 1 year for those who received additional education during the past 12 months. The only exception is that we do not treat "Industry certified training or certification courses" as additional education because those are more like adult and continuing training than formal education. Based on the above decision rules, we created a variable for the total number of years of schooling for all employees in all survey years.[7]

To address the endogeneity of education, we use changes in compulsory schooling laws over time to instrument for schooling. Changes in these laws have been shown to have significant effects on educational attainment, and have been a commonly-used instrument for education (see, for example, Acemoglu and Angrist, 2000; Lochner and Moretti, 2004; Milligan, Moretti and Oreopoulos, 2004; and Oreopoulos, 2006a, 2007).

Using the compulsory schooling laws data compiled by Oreopoulos (2006a, 2007), we first created three indicator variables to indicate whether the youngest school leaving age is 14, 15, or 16, and then created another three indicator variables to indicate whether the oldest school entry age is 6, 7, or 8. The linkage between the WES data and data on compulsory schooling laws is established based on the current province of residence of each individual and the year when the individual turned 14 for matching school leaving age or 6 for matching school entry age. Schmidt (1996) finds that the effects of compulsory schooling laws in the U.S. are largest when matched to individuals at age 14. The same procedure is used by Acemoglu and Angrist (2000), Lleras-Muney and Lichtenberg (2002), Schmidt (1996), and Goldin and Katz (2003) in their analyses of the U.S. data, and by Oreopoulos (2006a, 2007) in his analyses of Canadian data. Because WES does not report the birthplace of the respondents or the province of residence when

[7] We have also checked the sensitivity of our results to the following variation: the number of years of schooling increases by one if an employee received additional education during the past 12 months. There was little change, if any, in our results.

the respondents turned 6 or 14, we have to rely on the respondents' current province of residence at the time of the survey in linking WES data with data on compulsory schooling laws. [8] Although this might introduce some measurement error into our instrumental variables, previous studies suggest that such measurement error is not likely to seriously bias the IV estimates (Milligan, Moretti and Oreopoulos, 2004).

Relying on the instrumental variables thus created, we estimate the causal effects of high-school graduation and years of schooling on individuals' technology use and adoption. Identification of the causal effects of education is based on changes over time in the youngest school leaving age and oldest school entry age in a given province as well as variations in compulsory schooling laws across provinces. The identifying assumption is that conditional on province of residence, cohort of birth, and survey year, the timing of the changes in compulsory schooling laws within each province is orthogonal to unobserved characteristics that affect schooling choices, such as ability and family background.

Ideally, we would like to estimate a general model where the effect of education on technology use and adoption varies across years of schooling. Doing so, however, is not empirically feasible because the instruments we use are limited in both the range of schooling years affected and the amount of actual variation. Therefore, for the instrumental variable analyses, we use years of schooling or a dummy for high-school graduation as the main independent variables.

2.4 Sample Selection and Descriptive Statistics

In the analyses of each measure of technology use and adoption, we drop from the sample employees who have missing values on the dependent variable. Because WES does not report the specific provinces within the Atlantic region, we cannot link the compulsory schooling laws, that vary by province, with WES data for employees from the Atlantic region. These employees are therefore also dropped from the sample. We further exclude immigrants since their formal education was not influenced by Canadian compulsory schooling laws. These exclusions result in a final sample size of 101,612.

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[8] Individuals having moved across provinces before age 6 were mismatched for both the school leaving age and school entry age, while individuals having moved across provinces between age 6 and age 14 were mismatched for school leaving age. Because changes in compulsory schooling laws were unlikely to cause people to move across provinces, this should not cause significant bias in our estimates for the full sample.

As shown in Table 1, the average number of years of schooling completed by employees in our sample is 13.9, and the percentage of employees who graduated from high school is 84%. Table 1 also shows that the average years of work experience is 17.1 among employees in the sample. One thing to note is that we use actual work experience, not Mincer experience. WES provides information on actual work experience based on the following survey question: "Considering all jobs you have held, how many years of full-time working experience do you have?"

The mean of each of the four measures of technology use and adoption can be found in Tables 2 to 5. About two-thirds of employees used a computer in the job. Considering all jobs held, employees had used a computer in a work environment for an average of 7.4 years at the time of the survey. Fourteen percent of employees use a computer-controlled or computer-assisted technology in the course of normal duties while 26% of employees use any other machine or technological device, except computers, or computer-controlled or computer-assisted technology, for at least one hour a day.

There are substantial variations in technology use and adoption across industries and occupations. In the finance and insurance industry, for instance, 97% of the employees use a computer in the job, compared with only 43% for the construction industry. Wide variations are also evident in computer use across occupations, with the percentage of employees reporting computer use in the job ranging from 19% for production workers to 88% for professionals.[9] Given such large variations in technology use and adoption across industries and occupations, we decide to focus on the impact of education on technology use and adoption within industries and occupations. Therefore, we control for industry and occupation in the empirical analyses.

3 Empirical Framework

In order to quantify the effects of education on technology use and adoption, we pool cross-sectional data for employees linked with the workplace data from 1999 to 2005 and conduct OLS and IV estimations for each measure of technology use and adoption

[9] Given space limitations, the summary statistics of the four measures of technology use and adoption by industries and by occupations are not reported here, but are available on request.

separately. The advantage of analyzing the pooled cross-sectional data is the large sample size, which is particularly important for IV estimation.[10]

Given that our aim is to determine whether education has any causal role in technology use and adoption, rather than to determine the magnitude of its effect relative to the effects of other factors, we restrict our empirical model to a simple, reduced form specification as follows:

$$Tech\_Adopt_{ij} = \alpha + X_{ij}\beta + Y_j\gamma + Z_{ij}\eta + \varepsilon_{ij}\,, \tag{1}$$

where $Tech\_Adopt_{ij}$ is one of the four measures of technology use and adoption for worker i at workplace j; α is a constant; X_{ij} is a vector of explanatory variables for worker i at workplace j, including education, age, work experience, gender, marital status, union status, industry, occupation, province, and survey year; Y_j is a vector of workplace characteristics, including the three dummy variables for the size of the workplace; Z_{ij} is a vector of average observed skills of coworkers in the same firm and same occupation group, including education, experience, proportion under 30, proportion over 50, and proportion female; and ε_{ij} is a stochastic error component.

The reason for including Z_{ij}, the average observed skills of coworkers, in our empirical analyses is to partially control for unobserved ability of the individual worker. Under plausible assumptions about hiring and retention, workers with higher unobserved ability will tend to have coworkers with stronger average skills, which implies that some of the effects of unobserved ability can be eliminated by controlling for coworker skills.[11] This is possible in this study because WES is an employer-employee linked data set and provides information on the characteristics of coworkers. For those without any co-worker from the same firm and same occupation group, we replace their missing values on Z_{ij} with the mean of the non-missing observations.[12]

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[10] Although WES has a panel-data structure, we are not able to exploit it. Random effects estimates are not appropriate because the unobserved person-specific effects are likely to be correlated with educational attainment. Fixed effects (FE) estimates are appropriate in our setting, but the identification comes only from those individuals who changed their educational attainment during the past year. Due to the small variation in educational attainment across the two years in our sample, FE estimates are very imprecise.

[11] Card and de la Rica (2006) use a similar approach in their analyses of firm-level contracting and wage structure.

[12] Including an indicator variable for missing observations yields almost identical results.

When estimating Equation (1), we use the employee survey final weights provided by WES. The calculations of *t*-statistics and all inferences are based on robust standard errors. Calculation of standard errors takes into account potential correlations among employees within the same workplace by clustering by workplaces. Because the error terms in two adjacent years may be serially correlated due to the two-year panel feature of WES, we also cluster by employees to take into account the correlation between two observations on the same employee.[13] In addition, standard errors are clustered by province of residence and year of birth in all estimations.

4 Results

This section presents empirical evidence on the causal effects of education on the four measures of technology use and adoption based on data from WES (1999-2005).

4.1 The Effects of Education on Computer Use in the Job

In this subsection, we present and discuss our findings on the effects of education on a commonly-used measure of technology use and adoption—the probability of using a computer in the job. We begin by reporting the OLS estimates, and then the IV estimates.

4.1.1 OLS Estimates

Since the distribution of years of schooling is concentrated around 12 to 13 years, with a very small percentage of individuals having 8 years of schooling or less, we use 8 years of schooling or less as the base category and regress the probability of using a computer in the job on a complete set of years of schooling dummies.[14] The regression also controls for survey year, province, a quartic in age, five experience groups (years of experience 1-9, 10-19, 20-29, 30-39, and 40 or above), gender, marital status, union coverage, industry, occupation, size of the firm, and average characteristics of coworkers in the same firm and same occupation group, including education, experience, proportion under 30, proportion over 50, and proportion female.

Based on the OLS coefficient estimates on the complete set of schooling dummies, Figure 1 displays the association between education and the probability of using a computer in the job, controlling for other influences. The intercept applies to the base

[13] We use both observations on the same employee over two years based on the following grounds: some covariates may differ across two years; and the outcomes can differ from one year to another even if covariates do not differ or do not differ much.

[14] Because the percentage of the sample reporting more than 18 years of schooling was only 0.6%, we used the dummy variable for 19 years of schooling to cover all of those having more than 18 years of schooling.

category – average-age married males surveyed in 1999 who have 8 years of schooling or less, have 10 to 19 years of work experience, live in the province of Ontario, work in a primary product manufacturing industry as production workers, work in a firm of size 20-99 without union coverage, and have coworkers with average observed skills. The figure shows a steady increase in the probability of using a computer as schooling increases from 10 to 17 years, with a modest degree of concavity (suggesting diminishing returns to additional schooling).

In addition to the analyses where schooling is represented as a set of dummy variables, we also conduct analyses where the main independent variable is a dummy for high-school graduation or the number of years of schooling. OLS results from these regressions are presented in Columns (2) and (5) in Table 2 respectively. As shown in Column (2), graduating from high school is associated with a 13.8-percentage-point increase in the probability of using a computer in the job. Column (5) reveals that an additional year of schooling is associated with a 3.4-percentage-point increase in the probability of using a computer in the job. The coefficient estimates for the set of average observed skills of coworkers are consistent with our expectation. For example, both the average schooling and experience of coworkers have positive effects on computer use in the job.

Estimation results not reported in Table 2 further indicate that females, married people, workers not covered by unions, older workers, and individuals with more work experience are more likely to use a computer in the job than others. Conditional on all the other explanatory variables included in our analyses, employees from the following three industries are most likely to use a computer in the job: finance and insurance; information and cultural industries; and real estate, rental and leasing operations. Employees from the following three industries, on the other hand, have the lowest probability of using a computer in the job: construction; retail trade and consumer services; and forestry, mining, oil, and gas extraction. The probability of using a computer is located somewhere in between for the other industries. As for the impacts of occupation on the probability of computer use in the job, we find that clerical/administrative workers, managers, and professionals are most likely to use a computer in the job, whereas production workers are least likely to use a computer. Technical/trades workers and marketing/sales workers are somewhere in between. Consistent with findings from Wozniak (1987), we also find that the larger the size of the firm, the more likely that employees use a computer in the job.

For the purpose of comparison, we also conduct analyses without controlling for the average observed skills of coworkers. As shown in Columns (1) and (4) in Table 2, controlling for the average observed skills of coworkers results in a 6% decrease in the estimated effects of education. This could reflect the presence of unobserved variables that are correlated with both education and computer use in the job.

4.1.2 Instrumental Variable Estimates

The OLS estimates presented above are consistent with the hypothesis that education increases the probability of using a computer in the job. These estimates, however, may reflect the effects of unobserved individual characteristics that influence both the probability of computer use and schooling choices. Therefore, the positive correlations between the probability of computer use and education as shown by the OLS estimates may be biased and may not reveal the true causal link between the two.[15] By controlling for the average observed skills of coworkers, we may partially control for the unobserved ability of individual workers. This, however, is unlikely to fully address the endogeneity of education problem.

To deal with these potential biases, we use changes in compulsory schooling laws over time to instrument for schooling, as explained previously. Columns (3) and (6) in Table 2 presents the 2SLS estimates of the impact of education on computer use in the job with specifications identical to those used to obtain the OLS estimates when the endogenous variable is high-school graduation and years of schooling respectively. The upper panel of the two columns reports the first-stage results, i.e., coefficient estimates for the effects of different school leaving ages and school entry ages on educational attainment. The base categories are those with school leaving age of 14 and those with school entry age of 8. The second-stage results are presented in the lower panel of the table.

[15] It is also possible that the OLS estimates underestimate the effect of education on computer use due to, for instance, the existence of measurement error in educational attainment.

The first-stage results indicate that, in general, the more stringent the compulsory schooling legislation, the higher the probability of high-school graduation and the more years of schooling completed. Column (3) in Table 2 shows, for example, individuals who lived in provinces requiring the youngest school leaving age to be 15 when they were 14 were 9.2 percentage points more likely to have completed high school by the time of the survey compared with individuals living in provinces requiring the youngest school leaving age to be 14 when they were 14 years of age (the excluded category). Individuals who lived in provinces requiring the oldest school entry age to be six when they were six years of age were 6 percentage points more likely to have completed high school by the time of the survey compared with individuals who lived in provinces requiring the oldest school entry age to be eight when they were six (the excluded category). In addition, results in Column (6) indicate that the average years of schooling completed was 0.7 years higher for a youngest school leaving age of 15 than for a youngest school leaving age of 14, and 0.5 years higher for an oldest school entry age of 7 than for an oldest school entry age of 8. These results are similar to those obtained in Oreopoulos (2006a).

To assess the adequacy of the instrumental variables, we perform F-tests for exclusion of instruments in the first-stage regression. As shown in Columns (3) and (6) in the upper panel of Table 2, the F-statistic for exclusion of instruments is 5.7 with high-school graduation as the endogenous variable and 11.6 with years of schooling as the endogenous variable, which suggests significant positive correlations between the instruments and schooling.

Columns (3) and (6) in the bottom panel of Table 2 present instrumental variable estimates of the effects of high-school graduation and years of schooling on the probability of using a computer in the job. The IV coefficient for high-school graduation is 0.37 and is significant at the .10 level, indicating that graduating from high school increases the probability of using a computer in the job by 37 percentage points. The IV coefficient for years of schooling is 0.07 and significant at the .01 level, indicating that an additional year of schooling increases this probability by 7 percentage points. One thing to note is that the IV estimates are consistently higher than the OLS estimates. We discuss the differences between the IV and OLS estimates later in the paper.

4.2 The Effects of Education on Computer Use Experience

In this subsection, we present the empirical results on the effects of education on computer use experience based on analyses similar to those on computer use in the job as explained in detail in the previous section. Figure 2 displays regression-adjusted computer use experience by years of schooling based on the OLS estimates on the complete set of schooling dummies and additional controls. It shows a steady increase in the total number of years of experience in using a computer in a work environment as schooling increases from 10 to 19 years. The partial relationship also displays a modest degree of diminishing returns to additional education in the range 10 to 18 years of schooling.

Columns (1)-(2) and (4)-(5) in Table 3 present OLS estimates of the effects of high-school graduation and years of schooling respectively on the total number of years of experience in using a computer in a work environment based on two specifications. As shown in Column (2), conditional on all other explanatory variables including the average observed skills of coworkers, high-school graduates tend to have 2.8 more years of experience in computer use than those without a high-school degree. Column (5) reveals that an additional year of schooling is associated with an increase of 0.6 years in computer use experience. Comparisons of the specifications with and without the coworker variables indicate that the addition of these controls leads to a 3% decrease in the estimated effects of education.

Columns (3) and (6) in Table 3 present 2SLS estimates of the causal effects of high-school graduation and years of schooling on computer use experience. The first-stage results are exactly the same as those from the analysis of the probability of computer use in the job reported in Table 2, and thus not reported here. The second-stage IV coefficient is 6.2 for high-school graduation (P-value $< .10$) and 1.2 for years of schooling (P-value $< .01$), which indicates graduating from high school increases computer use experience by 6.2 years and an additional year of schooling increases computer use experience by 1.2 years. Employees with more education are not only more likely to use computers on the job at a point in time, but also start to use computers earlier in their working lives.

4.3 The Effects of Education on the Use of Computer-controlled or Computer-assisted Technology

Use of computer-controlled or computer-assisted technology also reflects a form of technology use in the workplace. OLS results reported in Columns (2) and (5) of Table 4 reveal that graduating from high school is associated with a 2.2-percentage-point increase in the probability of using computer-controlled or computer-assisted technology and that an additional year of schooling is associated with a 0.4-percentage-point increase in this probability. Both estimates are much smaller in magnitude than their counterparts for computer use, but are statistically significant at the .01 level.

The IV estimations, however, yield different inferences. As shown in Columns (3) and (6) of Table 4, the IV estimates are not significantly different from zero, suggesting that education does not exert a causal impact on the use of computer-controlled or computer-assisted technology. The OLS estimates thus appear to be misleading as they reflect correlations rather than causal impacts. We will discuss later in the paper why education may have a causal impact on some measures of technology use and adoption but not on others.

4.4 The Effects of Education on the Use of Technological Devices

As is the case with the analysis of the effects of education on the use of computer-controlled or computer-assisted technology, OLS and IV estimations yield different results on the effects of education on an employee's use of technological devices such as retail scanners and industrial machinery. According to the OLS estimates reported in Columns (2) and (5) in Table 5, education has a small negative impact on an employee's use of technological devices. Similar to the case of computer-controlled and computer-assisted devices, the IV estimates presented in Columns (3) and (6) in Table 5 are not significantly different from zero and suggest no causal impact of education on the use of technological devices. These results are discussed further in next section.

5 Discussions

5.1 Why Are Significant IV Estimates Higher than OLS Estimates?

The empirical results in this study based on the WES data indicate that the IV estimates are consistently higher than the corresponding OLS estimates when education exerts significant and positive impacts on technology use and adoption based on IV estimates.

Thus our results indicate that the causal effects of education on computer use and computer use experience are at least as large as, and perhaps larger than, would be suggested by standard OLS estimation. Many recent studies of the causal impacts of education on earnings have obtained similar results (e.g., Card, 2001). There are several potential explanations for this result.

One explanation is the existence of measurement error in educational attainment, which results in a downward bias in the OLS estimates (Griliches, 1977; Card, 2001).[16] An alternative explanation is that, in the presence of heterogeneity across individuals in the impacts of additional education, the OLS and IV estimates measure different treatment effects. OLS applied to a sample representative of the population estimates the average treatment effect (ATE), which corresponds to the expected impact of additional education for an individual chosen at random from the population. In contrast, IV generally estimates a local average treatment effect (LATE), which corresponds to the expected impact of additional education for the subset of the population whose behavior was altered by the instrument (Imbens and Angrist, 1994). In the case of instruments based on compulsory schooling laws, IV estimates the impact of additional education among those who obtained more schooling than they otherwise would have chosen to obtain as a consequence of changes in the laws.

A closely related explanation for the differences between the OLS and IV estimates is that there are non-linearities in the impacts of schooling on technology use and adoption. These non-linearities are evident from Figures 1 and 2, which indicate diminishing returns to additional education in the range 10 to 18 years of schooling, as well as above-average returns to education in the range 10-12 years of schooling. The instruments used in this study thus primarily influence educational attainment in the part of the educational distribution with above-average impacts of additional schooling. In the presence of these heterogeneous impacts, we expect the IV/LATE estimates to exceed the OLS/ATE estimates that pertain to the entire range of educational attainment.

To illustrate the above point, we re-estimate the OLS estimates reported in Column (5) of Tables 2 and 3 using different sub-samples based on years of schooling. In

[16] If, as is likely, the measurement error in educational attainment is non-classical in nature, the OLS estimates and IV estimates may both be inconsistent estimates of the returns to schooling (Kane, Rouse and Staiger, 1999).

both cases, the OLS point estimates based on the sub-sample with 10-12 years of schooling are very similar to the IV estimates reported in Column (6) of Tables 2 and 3. For example, when the outcome is computer use in the job, the OLS estimate using a sample restricted to those with 10-12 years of schooling is 0.061, which is much closer to the IV estimate of 0.068 than the original estimate based on the full sample (0.034). Similarly, for the analyses of computer use experience, restricting the sample to those with 10-12 years of schooling yields an OLS estimate of 0.885 (compared with 0.619 based on the full sample), which is closer to the IV estimate of 1.211 (see Column (6) of Table 3).[17] Thus it does not appear to be necessary to appeal to arguments that those affected by compulsory attendance laws were unusual in terms of the impacts of additional education relative to others with similar levels of completed schooling.

According to the above interpretation, any intervention that raises educational attainment in the neighborhood of high-school completion would yield above-average benefits in the form of more or earlier computer use on the job. Such non-linearities in the impacts of education on technology use and adoption are also consistent with the presence of "sheepskin effects" associated with the completion of a high-school diploma (12 years of schooling). Sheepskin effects have also been found in the impacts of education on earnings (Jaeger and Page, 1996; Ferrer and Riddell, 2002) and on crime (Lochner and Moretti, 2004).

5.2 The Relationship between Education and Technology Use in the Workplace

Studies of technological change and economic growth typically conclude that technological advances raise skill requirements in some occupations and jobs, but lead to de-skilling in others.[18] The relationship between formal education and the use of new technologies in the workplace likewise appears to be heterogeneous. Our IV estimates indicate that education exerts a positive influence on computer use in the workplace, but does not influence the use of computer-controlled and computer-assisted devices or other technological devices such as cash registers and sales terminals. In the context of the

[17] In his study of compulsory schooling in Great Britain and Ireland, Oreopoulos (2006b) also finds that the gap between the OLS and IV estimates can be attributed to non-linearities in the returns to schooling. Riddell and Song (forthcoming) obtain similar results in their analysis of the impacts of education on re-employment success among job losers.

[18] See, for example, Allen (1986) on the industrial revolution and Globerman (1986) on the automation period in the late 1950s and early 1960s.

current "information and communication technology" era, these results are consistent with the view that education increases the use of technologies that require or enable workers to carry out higher order tasks, whereas schooling does not affect the use of technologies that routinize workplace tasks. Case studies of the use of computers in the workplace are consistent with this conclusion (e.g. Levy and Murnane, 1996).

The finding that education has a causal impact on some measures of technology use and adoption but not others is consistent with the results in Dunne and Troske (2005). Dunne and Troske find that the correlation between the use and adoption of technologies and workforce skill at the plant level differs systematically by the task the technology performs. Specifically, they find that the likelihood of adopting a computer-aided design (CAD) machine used for design and engineering tasks is highly correlated with the proportion of skilled labor in the manufacturing facility whereas the use of CAD output to control manufacturing machines is uncorrelated with the plant-level skill mix. They also find similar results for networks.

Our finding is also consistent with findings from previous studies that technology is heterogeneous. Doms, Dunne, and Troske (1997), for instance, find that the relationship between skill upgrading and technology differs by the type of technology. In his extensive study of manufacturing firms on Long Island, Siegel (1999) separates technologies into two broad classes and finds that the magnitude of the effects of advanced technologies differs by the type of technology adopted.

6 Conclusions

In an environment characterized by rapid technological change as is the case today, studies on whether and how education promotes technology use and adoption and subsequently technology diffusion have become especially relevant. Relying on data from the Workplace and Employee Survey over the period 1999-2005, this study assesses the causal effects of education on technology use and adoption by using instrumental variables for schooling derived from Canadian compulsory school attendance laws.

We find that employees with more education are more likely to use computers on the job. Graduating from high school increases the probability of using a computer in the workplace by 37 percentage points and an additional year of schooling increases such probability by 7 percentage points, impacts that are large in size and statistically significant. We also find that employees with more education possess longer work experiences in using a computer. High-school graduates, for instance, have 6.2 more years of experience on average in using a computer at work than those without a high-school degree.

The impact of education on technology use in the workplace, however, differs by the type of technology. Our IV estimates imply that the hypothesis that education influences the use of computer-controlled or computer-assisted technology or the use of technological devices such as retail scanners or industrial machinery is rejected. Education has a causal impact on measures of technology use associated with higher order tasks undertaken by “knowledge workers” but does not influence the use of technologies associated with more routine tasks. Heterogeneity in the factors that influence technology use appears to be a feature of the modern workplace.

We also find evidence of heterogeneity in the impacts of education on computer use and computer use experience in the workplace. Impacts of additional schooling are largest in the range of 9 to 13 years of schooling, and somewhat lower above 13 years. The presence of heterogeneous effects helps to reconcile differences between OLS and IV estimates.

We conclude that the positive correlation between formal education and computer use in the workplace cannot be easily explained away by unobserved factors that are correlated with both variables. Findings from this study not only shed light on the causal relationships between education and individuals’ technology use and adoption, but also contribute to the literature on the non-market effects of education. Further, this study provides empirical evidence that supports education as a means to enhance technology adoption and diffusion, an important channel for technological advancement and economic growth. It also provides evidence of one possible mechanism by which changes in formal education can influence economic growth.

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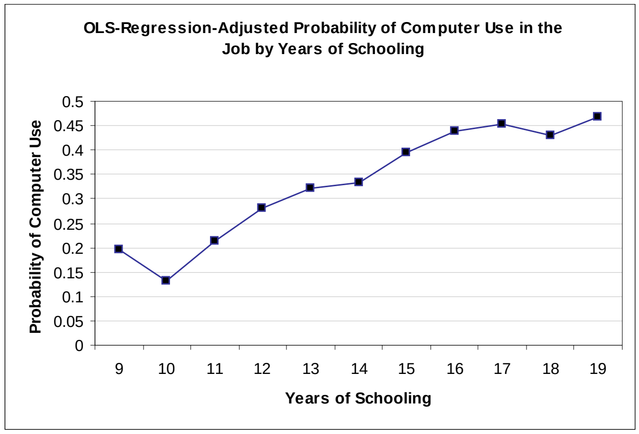
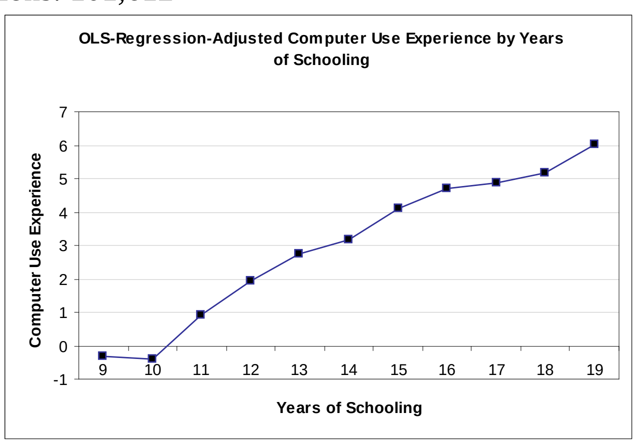
Figure 1
OLS-Regression-Adjusted Probability of Computer Use in the Job by Years of Schooling
Data source: Workplace and Employee Survey (1999-2005)
Number of observations: 101,612



Note: The OLS-regression-adjusted probability of computer use in the job is obtained by conditioning on survey year, province, a quartic in age, five experience groups (years of experience 1-9, 10-19, 20-29, 30-39, and 40 or above), gender, marital status, union coverage, industry, occupation, size of the firm, and average characteristics of coworkers in the same firm and same occupation group including education, experience, proportion under 30, proportion over 50, and proportion female.

Figure 2
OLS-Regression-Adjusted Computer Use Experience by Years of Schooling
Data source: Workplace and Employee Survey (1999-2005)
Number of observations: 101,612



Note: The OLS-regression-adjusted probability of computer use in the job is obtained by conditioning on survey year, province, a quartic in age, five experience groups (years of experience 1-9, 10-19, 20-29, 30-39, and 40 or above), gender, marital status, union coverage, industry, occupation, size of the firm, and average characteristics of coworkers in the same firm and same occupation group including education, experience, proportion under 30, proportion over 50, and proportion female.

Table 1
Descriptive Statistics for Analyses Based on Workplace and Employee Survey (1999-2005)
Number of observations: 101,612

Variable	*Mean*	*Std. dev.*
Years of schooling	13.933	2.279
High-school graduation	0.842	0.365
Age	39.750	11.330
Female	0.520	0.500
Unmarried	0.481	0.500
Years of work experience	17.062	11.010
Union	0.284	0.451
Firm size: 1-19	0.299	0.458
Firm size: 20-99	0.303	0.460
Firm size: 100-499	0.192	0.394
Firm size: 500 or more	0.206	0.404
Forestry, mining, oil, and gas extraction	0.018	0.133
Labor intensive tertiary manufacturing	0.040	0.197
Primary product manufacturing	0.036	0.186
Secondary product manufacturing	0.034	0.181
Capital intensive tertiary manufacturing	0.049	0.215
Construction	0.048	0.214
Transportation, warehousing and wholesale trade	0.108	0.311
Communication and other utilities	0.023	0.148
Retail trade and consumer services	0.237	0.425
Finance and insurance	0.048	0.214
Real estate, rental, leasing operations	0.019	0.136
Business services	0.090	0.287
Education and health services	0.216	0.412
Information and cultural industries	0.034	0.181
Managers	0.130	0.337
Professionals	0.164	0.370
Technical or trades	0.417	0.493
Marketing or sales	0.080	0.272
Clerical or administrative	0.143	0.350
Production workers	0.065	0.246
Average schooling of coworkers	13.933	1.718
Average experience of coworkers	17.849	7.255
Proportion under 30 among coworkers	0.185	0.266
Proportion over 50 among coworkers	0.197	0.247
Proportion female among coworkers	0.486	0.366
School leaving age = 14	0.037	0.188
School leaving age = 15	0.346	0.476
School leaving age = 16	0.617	0.486
School entry age = 6	0.694	0.461
School entry age = 7	0.263	0.440
School entry age = 8	0.040	0.195

Note: Calculations are weighted by the final employee weights.

Table 2
Estimates of the Effects of High-school Graduation and Years of Schooling on Computer Use in the Job
Data source: Workplace and Employee Survey (1999-2005)
Number of observations: 101,612

	Endogenous variable is high-school graduation			*Endogenous variable is years of schooling*		
	OLS	OLS	IV	OLS	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)
First stage						
School leaving age=15			0.092***			0.746***
			(0.026)			(0.143)
School leaving age=16			0.122***			0.865***
			(0.028)			(0.151)
School entry age=6			0.060**			0.230*
			(0.024)			(0.126)
School entry age=7			0.065**			0.461***
			(0.027)			(0.137)
F-statistic for exclusion of instruments			5.66			11.59
p-value			0.000			0.000
Second stage*: *Dependent variable is an indicator variable for whether the employee uses computer in the job.						
Mean of dependent variable: 0.647						
High-school graduation	0.146***	0.138***	0.370*			
	(0.012)	(0.012)	(0.202)			
Years of schooling				0.036***	0.034***	0.068***
				(0.002)	(0.002)	(0.025)
Average schooling of coworkers		0.023***	0.018***		0.020***	0.013**
		(0.003)	(0.005)		(0.003)	(0.006)
Average experience of coworkers		0.003***	0.003***		0.003***	0.003***
		(0.001)	(0.001)		(0.001)	(0.001)
Proportion under 30		0.009	0.017		0.005	0.005
		(0.016)	(0.018)		(0.016)	(0.016)
Proportion over 50		-0.046***	-0.042***		-0.048***	-0.048***
		(0.015)	(0.015)		(0.015)	(0.015)
Proportion female		-0.029***	-0.030***		-0.028**	-0.027**
		(0.011)	(0.012)		(0.011)	(0.011)

Note: All regressions control for survey year, province, a quartic in age, five experience groups (years of experience 1-9, 10-19, 20-29, 30-39, and 40 or above), gender, marital status, union coverage, industry, occupation, and size of the firm. Robust standard errors are reported in parentheses. All estimations correct for clustering by employee, workplace, province of residence, and year of birth, and are weighted by the final employee weights.
*Significant at the 10% level.
**Significant at the 5% level.
***Significant at the 1% level.

Table 3
Estimates of the Effects of High-school Graduation and Years of Schooling on Computer Use Experience
Data source: Workplace and Employee Survey (1999-2005)
Number of observations: 101,612

	Endogenous variable is high-school graduation			*Endogenous variable is years of schooling*		
	OLS	OLS	IV	OLS	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)
Second stage*: *Dependent variable is number of years using a computer at work.						
Mean of dependent variable: 7.362						
High-school graduation	2.834***	2.750***	6.164*			
	(0.150)	(0.150)	(3.202)			
Years of schooling				0.636***	0.619***	1.211***
				(0.029)	(0.029)	(0.399)
Average schooling of coworkers		0.257***	0.177**		0.201***	0.085
		(0.037)	(0.085)		(0.036)	(0.086)
Average experience of coworkers		0.029***	0.030***		0.025***	0.023**
		(0.009)	(0.009)		(0.009)	(0.009)
Proportion under 30		0.072	0.186		-0.023	-0.026
		(0.214)	(0.257)		(0.212)	(0.218)
Proportion over 50		-0.426**	-0.372*		-0.468**	-0.467**
		(0.211)	(0.219)		(0.213)	(0.220)
Proportion female		-0.662***	-0.677***		-0.635***	-0.620***
		(0.159)	(0.164)		(0.158)	(0.163)

Note: All regressions control for survey year, province, a quartic in age, five experience groups (years of experience 1-9, 10-19, 20-29, 30-39, and 40 or above), gender, marital status, union coverage, industry, occupation, and size of the firm. Robust standard errors are reported in parentheses. All estimations correct for clustering by employee, workplace, province of residence, and year of birth, and are weighted by the final employee weights.
*Significant at the 10% level.
**Significant at the 5% level.
***Significant at the 1% level.

Table 4
Estimates of the Effects of High-school Graduation and Years of Schooling on the Use of Computer-controlled or Computer-assisted Technology
Data source: Workplace and Employee Survey (1999-2005)
Number of observations: 101,612

	Endogenous variable is high-school graduation			*Endogenous variable is years of schooling*		
	OLS	OLS	IV	OLS	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)
Second stage: Dependent variable is an indicator variable for the use of computer-controlled or computer-assisted technology.						
Mean of dependent variable: 0.135						
High-school graduation	0.020***	0.022***	0.038			
	(0.008)	(0.008)	(0.123)			
Years of schooling				0.004***	0.004***	0.002
				(0.001)	(0.001)	(0.016)
Average schooling of coworkers		-0.005**	-0.005		-0.005**	-0.005
		(0.002)	(0.004)		(0.002)	(0.004)
Average experience of coworkers		-0.001	-0.001		-0.001	-0.001
		(0.000)	(0.000)		(0.000)	(0.000)
Proportion under 30		0.021	0.021		0.020	0.020
		(0.013)	(0.013)		(0.013)	(0.013)
Proportion over 50		-0.007	-0.007		-0.008	-0.008
		(0.010)	(0.010)		(0.010)	(0.010)
Proportion female		0.005	0.005		0.005	0.005
		(0.008)	(0.008)		(0.008)	(0.008)

Note: All regressions control for survey year, province, a quartic in age, five experience groups (years of experience 1-9, 10-19, 20-29, 30-39, and 40 or above), gender, marital status, union coverage, industry, occupation, and size of the firm. Robust standard errors are reported in parentheses. All estimations correct for clustering by employee, workplace, province of residence, and year of birth, and are weighted by the final employee weights.
*Significant at the 10% level.
**Significant at the 5% level.
***Significant at the 1% level.

Table 5
Estimates of the Effects of High-school Graduation and Years of Schooling on the Use of Technological Device
Data source: Workplace and Employee Survey (1999-2005)
Number of observations: 101,612

	Endogenous variable is high-school graduation			*Endogenous variable is years of schooling*		
	OLS	OLS	IV	OLS	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)
Second stage: Dependent variable is an indicator variable for the use of any other machine or technological device for at least one hour a day, except computers, or computer-controlled or computer-assisted technology.						
Mean of dependent variable: 0.255						
High-school graduation	-0.028***	-0.026***	0.205			
	(0.010)	(0.010)	(0.163)			
Years of schooling				-0.005***	-0.004**	0.000
				(0.002)	(0.002)	(0.022)
Average schooling of coworkers		-0.005**	-0.010**		-0.005**	-0.005
		(0.002)	(0.004)		(0.002)	(0.005)
Average experience of coworkers		0.000	0.000		0.000	0.000
		(0.001)	(0.001)		(0.001)	(0.001)
Proportion under 30		-0.007	0.000		-0.006	-0.006
		(0.015)	(0.016)		(0.015)	(0.015)
Proportion over 50		-0.015	-0.012		-0.015	-0.015
		(0.014)	(0.014)		(0.014)	(0.014)
Proportion female		0.011	0.010		0.011	0.011
		(0.010)	(0.011)		(0.011)	(0.011)

Note: All regressions control for survey year, province, a quartic in age, five experience groups (years of experience 1-9, 10-19, 20-29, 30-39, and 40 or above), gender, marital status, union coverage, industry, occupation, and size of the firm. Robust standard errors are reported in parentheses. All estimations correct for clustering by employee, workplace, province of residence, and year of birth, and are weighted by the final employee weights.
*Significant at the 10% level.
**Significant at the 5% level.
***Significant at the 1% level.

Table 6
OLS Estimates of the Effects of Years of Schooling on Computer Use in the Job and Computer Use Experience based on Restricted Samples
Data source: Workplace and Employee Survey (1999-2005)

	Coefficient estimate		
Sample	Outcome is computer use in the job	Outcome is computer use experience	*No. of ob.*
Full Sample	0.034***	0.619***	101,612
	(0.002)	(0.029)	
Schooling < 16	0.033***	0.601***	79,868
	(0.003)	(0.037)	
Schooling < 13	0.021***	0.414***	30,454
	(0.005)	(0.054)	
9 < Schooling < 16	0.041***	0.718***	75,988
	(0.003)	(0.051)	
9 < Schooling < 13	0.061***	0.885***	26,574
	(0.011)	(0.127)	

Note: All regressions control for survey year, province, a quartic in age, five experience groups (years of experience 1-9, 10-19, 20-29, 30-39, and 40 or above), gender, marital status, union coverage, industry, occupation, size of the firm, and average characteristics of co-workers in the same firm and same occupation group. Robust standard errors are reported in parentheses. All estimations correct for clustering by employee, workplace, province of residence, and year of birth, and are weighted by the final employee weights.
*Significant at the 10% level.
**Significant at the 5% level.
***Significant at the 1% level.