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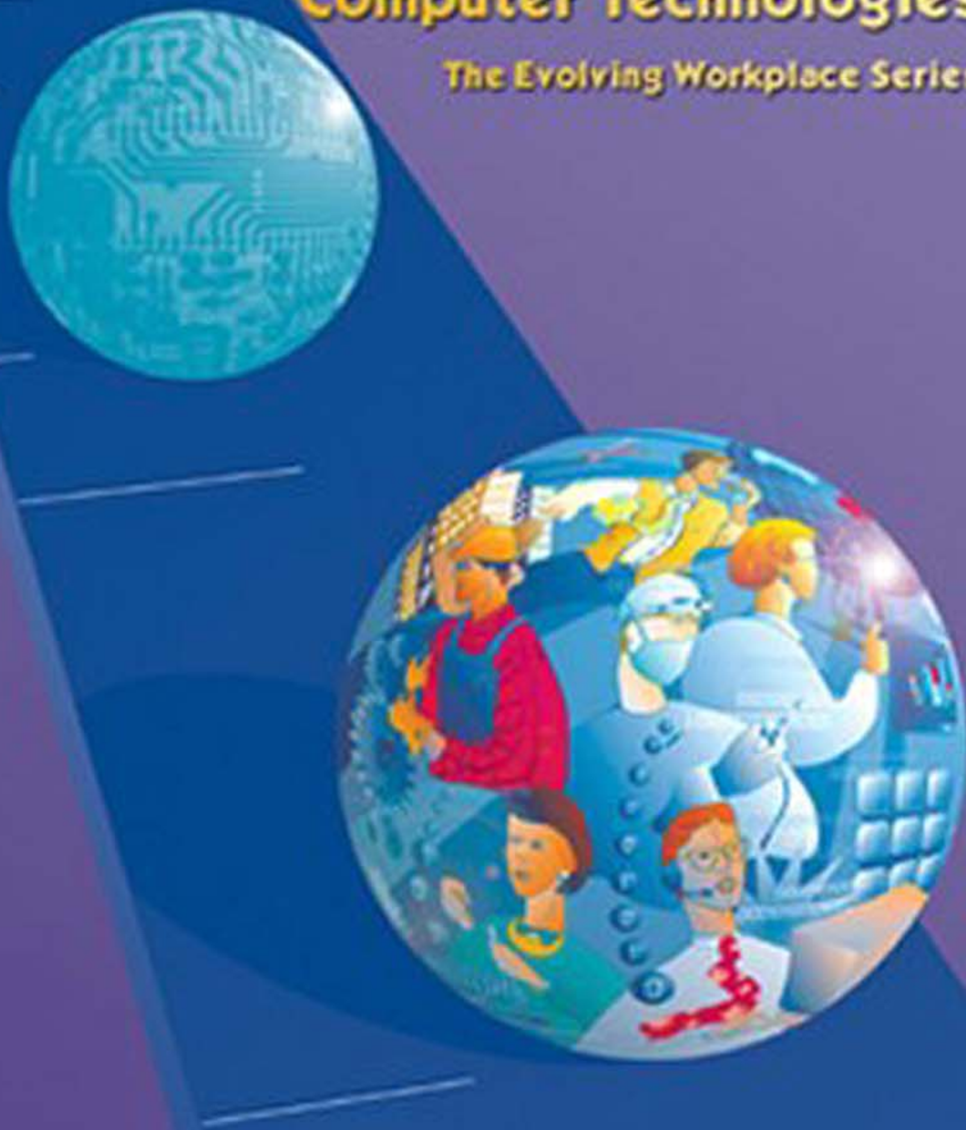
Working Smarter: The Skill Bias of Computer Technologies

The Evolving Workplace Series



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Foreword

This document provides data from the new Workplace and Employee Survey (WES) conducted by Statistics Canada with the support of Human Resources Development Canada. The survey consists of two components: (1) a workplace survey on the adoption of technologies, organizational change, training and other human resource practices, business strategies, and labour turnover in workplaces; and (2) a survey of employees within these same workplaces covering wages, hours of work, job type, human capital, use of technologies and training. The result is a rich new source of linked information on workplaces and their employees.

Why have a linked workplace and employee survey?

Advanced economies are constantly evolving. There is a general sense that the pace of change has accelerated in recent years, and that we are moving in new directions. This evolution is captured in phrases such as "the knowledge-based economy" or "the learning organization". Central to these notions is the role of technology, particularly information technology. The implementation of these technologies is thought to have substantial impact on both firms and their workers. Likely related to these technological and environmental changes, many firms have undertaken significant organizational changes and have implemented new human resource practices. Globalization and increasing international competition also contribute to the sense of change.

In this environment, greater attention is being paid to the management and development of human resources within firms. Education and training are increasingly seen as an important investment for improved prosperity—both for firms and individual workers.

Thanks to earlier surveys, researchers have a good understanding of workers' outcomes regarding wages and wage inequality, job stability and layoffs, training, job creation, and unemployment. What is missing on the employees' side is the ability to link these changes to events taking place in firms. Such a connection is necessary if we hope to understand the association between labour market changes and pressures stemming from global competition, technological change, and the drive to improve human capital. Thus, one primary goal of WES is to establish a link between events occurring in workplaces and the outcomes for workers. The advantage of a linked survey is depicted in the figure which displays the main content blocks in the two surveys.

The second goal of the survey is to develop a better understanding of what is indeed occurring in companies in an era of substantial change. Just how many companies have implemented new information technologies? On what scale? What kind of training is associated with these events? What type of organizational change is occurring in firms? These are the kinds of issues addressed in the WES.

This report aims to give those interested in computer technologies and skills some useful insights from the initial survey, as well as stimulating their interest in the possibilities provided by these new data.

Link between the workplace survey content, employee survey content, and outcomes

Employee outcomes:

- wage/earnings/hours polarization;
- wage levels by worker type;
- training received;
- use of technologies;
- job tenure.

Workplace characteristics:

- technology implemented;
- operating revenues and expenditures, payroll, and employment;
- business strategies;
- unionization;
- compensation schemes;
- training provided;
- mix of full-time/part-time, contract, and temporary employees;
- organizational change;
- subjective measures of productivity, profitability, etc;
- type of market in which firm competes.

Worker/job characteristics:

- education;
- age/gender;
- occupation, management responsibilities;
- work history, tenure;
- family characteristics;
- unionization;
- use of technology;
- participation in decision making;
- wages and fringe benefits;
- work schedule/arrangements;
- training taken.

Workplace outcomes:

- employment growth;
- growth in revenues;
- organizational change;
- implementation of technologies;
- changing human resource practices.

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Introduction

Computers have come to have an enormous presence in Canadian workplaces. In 1999, 70% of Canadian workplaces (accounting for 90 % of employment) had at least one computer user. Moreover, six out of ten workers regularly use a computer on the job. This compares to just three out of ten in 1990. So in less than a decade, computer usage among Canadian workers has doubled.

Such a major change in the way work is conducted has not escaped the attention of economists, business analysts and labour market researchers. The rapid diffusion of computers and computer-based technologies has spawned a number of lines of inquiry. Some wonder why expanding computer usage has not been accompanied (at least until recently) by similar increases in productivity—the so-called productivity paradox. Others are more concerned with the complementarity of human capital (education and work skills) and physical capital (buildings and machines). Endogenous growth theories hypothesize that economic growth is enhanced when the quality or quantity of both types of capital increases in tandem. But what happens if the growth in one type of capital outpaces the rate of change in the other? The situation whereby the implementation of computers and computer-based technologies exceeds the growth of computer skills in the labour force has received particular attention in recent years.

Classical economic analysis implies that if the demand for a particular type of labour (e.g. computer literate workers) increases faster than the supply, then the price (computer literate workers' earnings) will increase relative to workers who do not possess the requisite computer skills. This process has been termed *skill-biased technological change*. Although the literature on skill-biased technological change developed initially as an explanation for the increasing gap between the earnings of more- and less-educated workers in the United States, it has subsequently been examined in the context of most advanced economies.

If one was to assess the body of evidence in favour of the skill-biased technological change hypothesis in the language of a courtroom drama, there seems to be ample circumstantial evidence but no smoking gun. The demand side and supply side trends seem to have the appropriate timing (most strongly demonstrated in the United States). And studies combining plant-level measures of technology change and aggregate proxies for employee skills (e.g. ratio of white-collar to blue-collar workers) add further grist to the mill. Yet data that combine plant-level technology information with individual-level information on education, training, wages and technology use have not been available to date.

Although this study does not purport to have found the smoking gun, it does make use of a new source of data—the Workplace and Employee Survey (WES)—that contains information salient to the examination of the skill-biased technological change hypothesis. Most importantly, this survey provides a framework in which information on individual workplaces can be analysed in concert with information on individual employees within those workplaces.

Of particular interest to this study are data covering:

- major computer hardware and software implementations in workplaces that span a broad cross-section of the economy;

- training efforts of hardware/software implementers versus other workplaces; and,
- information on the education, computer use and demographics of employees in the sampled workplaces.

These data enable the examination of the skill-biased technological change hypothesis at the business location level, encompassing employees within those locations.

Although these data provide an interesting new perspective on the issue of skill-biased technological change, it is also important to point out their limitations. Note that the general debate focuses on changes in technology and changes in the demand for the highly skilled workers. This study uses only the initial 1999 cross-section of the WES sample and thus cannot directly address questions that pertain to longer run changes in technology and labour supply.[1] Thus the results do not infer the direction of causation in the relationships nor do they account for lagged effects which may appear (and/or accumulate) over longer time spans. It should also be pointed out that WES does not contain a measure of current capital stock (computer or otherwise), so current computer investment may not be an accurate indicator of the employer's technological proficiency. These data will improve as the WES panel is tracked over time.

Within the broader debate, then, our focus will be quite specific. The report will address the following questions:

1. Do computer hardware and software implementers spend more per employee on training than non-implementers?

[1] The 1999 WES cross-sectional employer sample will be followed over time, creating the opportunity for more rigorous studies as the panel progresses.

2. Do computer hardware and software implementers have more highly educated workforces than non-implementers?
3. Are highly educated workers more likely to be found in hardware/software implementing workplaces?
4. Are recently hired workers in hardware/software implementing workplaces better educated than their longer-tenured co-workers?

Note that although the second and third questions are very similar in nature, the second will make use of the employer data while the third will draw on the employee data. In essence, this allows us to examine whether the employer and employee perspectives on skill-biased technological change corroborate one another. The results are comprised mainly of regression results. These should not be interpreted as tests of formal models nor indicators of the direction of causation, but rather as conditional means and distributions that account for many of the employer and employee variables related to computer technology, training and education.

The paper begins with a literature review of the salient contributions to the skill-biased technological change debate. Second, the descriptive and multivariate results are presented. Finally, a concluding discussion orients the results within the broader literature and suggests avenues for further research.

Literature Review

The process of skill-biased technological change is a dynamic one, where the adoption or evolution of new technology or of the stocks and marginal investment in computer hardware and software are hypothesized to precipitate both increases in training and increases in the demand for more educated workers (Berman, Bound and Machin, 1997; Kahn and Lim, 1998; Burris, 1998). The demand for and wages of less skilled workers should decline concomitantly (Autor, Katz and Krueger, 1997).

To capture the component of change, the ideal investigation of this process would therefore require longitudinal data on firms. It would track changes in the level and sophistication of computer stock and investment in technology, changes in the level of training provided, and changes in the educational level and composition of the employees. Both the time component and the firm level of the analyses are important for establishing the causal order and causal association. Skill-biased technological change would be demonstrated if firms with a strong orientation towards technology (as evidenced by their existing computer stock and/or their increased investment in computer technology) experienced a subsequent increase in training as well as an increase in the educational level of its employees, or at least an increase in the educational requirements for new hires. In previous research, such analyses have not been possible because no study to date has possessed this ideal data. This section will briefly review the existing evidence and outline several gaps in the literature that this report will address.

Skill-biased technological change was originally proposed in the United States as an explanation for the increase in wages of higher skilled workers relative to lesser skilled workers through the 1980s (Bound and Johnson, 1992; Berman, Bound and Griliches, 1994). The research, primarily focused on manufacturing industries, produced compelling evidence that increasing demand for college educated workers accounted for a growing wage gap by education. For example, John Bound and George Johnson (1992) examine wage rates and education levels across a number of industries using the 1973-1974, 1979 and 1988 U.S. Current Population Survey. They demonstrate that the strongest factor in the increase of the relative wages of higher skilled workers and the relative decrease in wages of less skilled workers was technological change that favoured more educated labour over less educated labour.

International evidence supports the U.S. data and demonstrates that these trends are pervasive across both industries (within the U.S.) and other OECD countries (Berman, Bound and Machin, 1997; Machin and Van Reenen, 1998). An industry's average education and its proportion of workers who use computers is associated with its research and development intensity (Machin and Van Reenen, 1998). Moreover, the increased demand for educated workers and the wage premium associated with higher educated workers appear to be strongest in industries with the most technological change (Allen, 1996; Bartel and Sicherman, 1997).

The same phenomenon has been observed in Canada—industries with more technological change tend to have more highly educated and more highly paid workers (Baldwin, Gray and Johnson, 1997; Bartel and Sicherman, 1997).[2] Baldwin and Da Pont (1996) present evidence that,

[2] Hughes and Lowe (2000) provide a notable exception, concluding that computer use is not associated with skill level and earnings after controlling for occupational prestige, age, and employment status.

as firms introduce new technology, their skill requirements increase (also see Baldwin, 1999). However, research in Canada on skill-biased technological change remains tangential: most evidence is gleaned from research focused on related topics such as skill polarization, firm innovation, or trends in workplace technology (Hughes and Lowe, 2000; Myles, 1988; Economic Council of Canada, 1991; McMullen, 1996). It is clear that technologically-oriented firms are more committed to training (Baldwin, 1999; Baldwin and Johnson, 1995, 1997) and have higher wage rates (Baldwin and Da Pont, 1996; Baldwin, Gray, and Johnson, 1997). What is needed is an integrative study that examines the relationship between the introduction of technology, training and education. This report addresses this gap.

Methodological issues

This report will also address several methodological limitations that confront the literature on skill-biased technological change. The issues relate to (1) the measures of technology and skill, and (2) the level of aggregation used and the range of industries considered.

Measuring Technology and Skill

First, many studies have used less than optimal measures of technology change. Indicators such as proportion using computers (Autor, Katz, and Krueger, 1997; Haskel and Heden, 1999), ratio of research and development (R&D) funds to net sales (Bartel and Sicherman, 1997), number of patents used in industry (Bartel and Sicherman, 1997), real output/real capital stock (Bartel and Lichtenberg, 1987), and number of production related technologies used in past year (Doms, Dunne and Troske, 1997) do not directly measure technological change. A more direct measure would reference specific changes at the workplace or industry level.

Similarly, skill has been an elusive concept. The concern with skill-biased technological change has focused attention on the role of education. Education is an appropriate measure of skill since employers themselves use education as an indicator of an employee's technological competency and his/her ability to learn and to adapt to continuing technological change (Baldwin, Gray and Johnson, 1997; Levy and Murnane, 1996; Bartel and Lichtenberg, 1987). However, previous researchers have not been so fortunate to have such educational data to compare with their data on technological change. Instead, skill is often operationalized as the distinction between manual and non-manual workers, or between production and non-production workers (Berman, Bound and Machin, 1997; Haskel and Heden, 1999). When education is available, it is usually a two category measure that distinguishes those with high school from those without (Bartel and Lichtenberg, 1987), or those with a college degree from those without (e.g. Autor, Katz and Krueger, 1997; Bartel and Lichtenberg, 1987; Doms, Dunne, and Troske, 1997; Bartel and Sicherman, 1997).

Some studies focus more on learning in the workplace, measuring training provided by the employer as an indicator of the skill of its workers (Balwin and Johnson, 1995). Although this is one of the less direct measures of skill, assessing training is an important component in the process of skill-biased technological change. Skill-biased technological change may engender a greater commitment by firms to train their already highly skilled employees. In fact, Acemoglu (1998) suggests that skilled workers are the causal agent that drive technological change, not vice versa. Since both types of indicators provide important information about the skill composition of the labour force, future research would benefit from analyses that include a more comprehensive measure of employee education as well as including information about training offered by employers and training received by employees.

Level of Aggregation and Range of Industries

The more precisely one can assess skill and technological change, the better for understanding the underlying process of interest. Because of data limitations and different research interests, many previous studies were able only to paint with broad brush strokes, outlining correlations between skill and technological advancement across industries (Allen, 1996; Autor, Katz and Krueger, 1997; Baldwin and Johnson, 1995; Baldwin, Gray and Johnson, 1997; Baldwin, 1999; Machin and Van Reenen, 1998). The process can only be inferred at this level. These studies can not examine finer distinctions that may occur *within* an industry when some firms are more committed to technology than others (Baldwin, 1999).

Studies at the establishment, firm, or workplace level permit research that examines the process of skill-biased technological change more precisely. For example, using panel data, Haskel and Heden (1999) found that as establishments computerized, their demand for more highly skilled workers increased and for manual workers decreased.

Research that examines how the employer's or industry's technology is associated with an employee's skill can specify the patterns even more closely. Such research has been done comparing industry technological change and individual wages (Bartel and Sicherman, 1997) and between computer capital per worker and individual wages (Autor, Katz and Krueger, 1997). These studies provide support that the industry level trends identified earlier hold when more precise measurement is used. However, research in this vein that focuses on workplace level dynamics of employer technology and training, and employee skill is a gap that remains.

Specifically, research is needed to examine whether higher skilled workers are more likely to be employed in high tech firms and/or more likely to receive training from their employers than less skilled workers. The above studies do not distinguish whether the employees use the technology or whether they receive the training reported by the firm. The industry level analyses do not even distinguish whether the employees with higher education work for the firms who implement technology or not. Thus, research is needed that focuses on whether employees with more education receive more training and work in establishments which introduced a new technology. Consistent with the above discussion regarding employers, employees' experiences with training can be indicated by the type of training they received (general or computer/ technology related) and by the form of training (formal, on-the-job, or outside the job).

Finally, many studies are limited to manufacturing industries (Baldwin and Da Pont, 1996; Baldwin, Gray, and Johnson, 1997; Bartel and Sicherman, 1997; Berman, Bound and Griliches, 1994; Haskel and Heden, 1999; Kahn and Lim, 1998; Machin and Van Reenen, 1998) but notable exceptions are Autor, Katz, and Krueger (1997); Allen (1996); Bound and Johnson (1992). Given that computers and information technology are pervasive across a wide range of industries, it is important for future research to use data that do not exclude many of the people affected by technological change. This report addresses this limitation by including a wide range of industries.

Do Computer Technology Implementers Offer More Training than Non-implementers?

At its core, the skill-biased technological change hypothesis assumes that computer literacy (the skill to perform workplace-related computing tasks) is a scarce commodity. Thus implementations of new computer-based technologies should increase the demand for employee training—the most immediate method of acquiring scarce skills. Note that this does not necessarily distinguish computers from other types of technologies, since the skill required to operate a new printing press, for example, may also be scarce. However, unlike many skill-intensive technologies, computers are ubiquitous across a broad range of industries and so have a correspondingly greater impact on the overall demand for skills. Furthermore, computer hardware and, particularly, computer software generally have shorter life spans than other forms of capital, thereby stimulating the need for continual training. According to the WES, about 23% of workplaces introduced at least one major new hardware and/or software technology in the previous year. The regional and industrial distributions of these computer technology implementers can be found in Appendix C.

The WES data indicate that significantly higher levels of training coincide with these adoptions of computer technologies. About half (50.6%) of workplaces that adopted computer technology provided computer-related training in 1999, almost three times the rate of 17.7 % among those that did not. But much of this gap is due to the greater

Table 1

Proportion of employees who received training by workplaces' cost per employee of computer-based technology adoption

	No computer-based technology adoption	Computer-based technology adoption	Cost of implementation = \$1 to \$699/employee	Cost of implementation = \$700 to \$2,499/employee	Cost of implementation = \$2,500 or more/employee
			%		
Computer-related training	14.1	23.0	19.3	26.3	31.6
Classroom	8.5	13.7	11.6	14.3	19.3
On-the-job	6.9	11.7	9.5	14.5	15.2
Other type of training	44.3	45.6	47.8	41.1	44.4
Classroom	29.6	30.7	32.5	26.6	29.8
On-the-job	23.0	23.5	24.5	21.1	23.1

Source: Workplace and Employee Survey 1999.

propensity of large establishments to both invest in hardware and/or software and provide computer-related training.

Thus it is also important to look at computer-related training from the employee perspective, which removes much of the large establishment bias. This bias exists since larger employers are very likely to have some form of employee training, even though not many employees may be involved in any period. So it makes sense to look at the incidence of training from the employee's perspective to control for this bias. From this point of view, 23% of the employees in workplaces with new hardware and/or software received some computer-related training, compared with 14% in those that had not implemented any technology (Table 1). So employees of hardware and/or software adopters are more than one-and-a-half times as likely to receive computer-related training compared to

Table 2

Proportion of computer users who received training by workplaces' cost per employee of computer-based technology adoption

	No computer-based technology adoption	Computer-based technology adoption	Cost of implementation = $1 to $699/employee	Cost of implementation = $700 to $2,499/employee	Cost of implementation = $2,500 or more /employee
			%		
Computer-related training	23.6	32.7	29.3	37.9	36.0
Classroom	14.2	19.6	18.1	20.8	22.1
On-the-job	11.7	16.4	14.1	21.0	17.2

Source: Workplace and Employee Survey 1999.

employees of other establishments. Furthermore, the incidence of training increased with the per employee cost of the hardware and/or software implemented. Almost one-third (32%) of employees in businesses which paid $2,500 or more per employee for a new technology implementation received training compared with 19% of employees in workplaces which spent up to $700.

Another potential source of bias in training comparisons relates to differences in computer use: two-thirds of the employees in implementing establishments use computers, compared with just over a half (56%) in non-implementing establishments. Therefore it is possible that the elevated training rates of computer technology adopters could be due to the simple fact that they have a greater concentration of computer users. But the same result persists when looking only at computer users: those in technology adopters were 39% more likely to receive computer-related training than computer users in other establishments (Table 2).

It is also possible that this elevated training rate could be related to some other characteristics of computer technology adopters. As such, the probability that an employer offers computer-related training was fit on a number of location characteristics using a logistic regression model (see Appendix D). The adoption of computer technology effect remains significant even after controlling for location size, industry, computer usage, collective bargaining coverage, number of competitors and regional unemployment rate. So computer technology adoptions generally are associated with higher levels of computer-related training.

If computer implementations do lead to a higher level of training in the workplace then why should we be concerned with education—workers could be getting all the computing know-how they require through training. Although computer training may be available for any class of worker, it will generally be more efficient for those who have "learned how to learn". This would particularly hold true where frequent training episodes are required to keep up with evolving technologies or where employees may be relied upon to train themselves. For example, the WES indicates that 57% of university graduates taught themselves how to use their main computer applications, compared to about 40% of those with lower levels of education.

It is also possible that there is a feedback loop by which a highly educated workforce might influence further computer investments. To wit, highly educated workers might be more adept at finding technological solutions to workplace problems and so may influence their employers to spend more on computer hardware and software.

Are Workplaces with Highly-educated Employees More Likely to Implement Computer-based Technologies?

To address this question, we first look at the distribution of employee education within workplaces with varying levels of hardware and/or software implementation, calculated on a per employee basis (Table 3). Workplaces spending more money per employee on the implementation of new hardware and/or software computer technologies tend to have a better educated workforce. Note that the proportion of employees with less than a high school diploma declines as hardware/software implementation costs intensify (reading across the first two rows of Table 3). In contrast, the workplace share of university graduates increases with the level of computing investment: university graduates comprised 17% of workplaces that had no major computer investments compared to 22% of workplaces that spent $2,500 or more per employee on hardware/software.

When education is further disaggregated into a 28-level semi-continuous variable (see Appendix B, for details), the association between education and hardware/software technology is confirmed. Workplaces that did not implement a technology have a significantly lower average level of education among their workers, 16.6, than workplaces who did implement a technology, 17.1 (Table 4). The significant difference in employee education is most evident between workplaces who spent less than $2,500 per employee compared with those who spent $2,500 or more per employee (Table 5).

Table 3

Hardware/software technology implementation intensity, by employee education

Education	Hardware/software implementation intensity ($ per employee)			
	$0	$1 to $699	$700 to $2,499	$2,500 or more
			%	
Never attended/primary	3.03	2.69	1.59	1.05
High school, without diploma	11.27	10.65	8.71	6.76
High school, with diploma	21.31	20.53	21.15	19.93
Non-university post-secondary	37.91	37.57	36.78	39.04
Some university	9.63	9.20	10.54	11.41
University degree +	16.86	19.37	21.23	21.82
Total	**100.00**	**100.00**	**100.00**	**100.00**

Chi square significant p < .001.
Source: Workplace and Employee Survey 1999.

Table 4

Means and standard errors for education and other employee variables, by hardware/software implementation

	No hardware/ software implementation		Any hardware/ software implementation
Employee education	16.60	**	17.10
	(.09)		(.13)
	N = 14,440		N = 9,562
Workplace total number of employees	12.03	***	22.12
	(.32)		(1.13)
	N = 4,186		N = 2,160
Employer training costs per employee	92.54	***	188.03
	(7.84)		(19.81)
	N = 4,186		N = 2,160
Employee age	38.96	**	40.29
	(.28)		(.32)
	N = 14,440		N = 9,562
Employee years of work experience	15.57	***	16.79
	(.24)		(.28)
	N = 14,440		N = 9,562

* p < .05; ** p < .01; ***p < .001
Standard Errors in parentheses.
See Appendix B for details on the construction of the education variable.
Source: Workplace and Employee Survey 1999.

Table 5

Means and standard errors of education (semi-continuous), by hardware/ software implementation intensity (N = 24,002)

Hardware/software implementation intensity ($/employee)	Education		
	Mean	Standard error	N
None, $0	16.60	.09	14,440
Low, $.01 to $699	17.02	.19	5,241
Medium, $700 to $2,499	16.79	.27	2,515
High $2,500 or more	17.82	.25	1,806

Anova results: None-low, $p < .05$; None-medium, not significant; None-high, $p<.001$; Low-medium, not significant; Low-high, $p < .05$; Medium-high, $p < .01$.
See Appendix B for details on the construction of the education variable.
Source: Workplace and Employee Survey 1999.

Although average education level among implementing workplaces is higher than in other workplaces, the difference is not great in absolute terms. In fact, the differences in education levels may be related to other differences between computer technology implementers and other businesses. For example, workplaces that introduced a new hardware/ software technology in the past 12 months are larger and spend more on overall training per employee (Table 4). Furthermore, their employees are older and have more years of work experience. There are also variations by region and industry between establishments that did and did not introduce a new technology. So it is possible that if we constructed cross-tabulations incorporating these variables, the educational differences between implementers and non-implementers might disappear. However, such tables would be unwieldy and rife with small cell sizes. Instead, we turn to multivariate regression techniques to account for the effects of intervening variables (location size, industry and region). These are presented in the spirit of conditional means and distributions, rather than formal econometric models, since we do not yet have the longitudinal

Table 6

Employers' hardware/software investments related to employees' education
Log odds and odds ratios (parentheses) from ordered logit models

Selected variables	Model 1 education	Model 2 training	Model 3 education, training	Model 4 education, training, size	Model 5 = Model 4 + industry, region	Model 6 = Model 5 + experience, gender, age
Education	.05***		.04**	.04**	.03*	.03*
	(1.05)		(1.04)	(1.04)	(1.03)	(1.03)
Low training per employee		.38*	.40*	.38*	.35*	.35*
($1-199)		(1.47)	(1.49)	(1.46)	(1.42)	(1.42)
Medium training per employee		1.00***	.98***	.96***	.87***	.87***
($200-599)		(2.72)	(2.66)	(2.62)	(2.38)	(2.38)
High training per employee		.79***	.74***	.73***	.48*	.48*
($600+)		(2.20)	(2.10)	(2.07)	(1.62)	(1.62)

*p <.05; ** p < .01; *** p < .001
The reference category is *no training expenditures*.
Source: Workplace and Employee Survey 1999.

data necessary to fully examine the skill-biased technological change hypothesis.

To examine whether the introduction of new hardware/software technology is associated with employee education and training controlling for other relevant variables, ordered logit models were estimated (Table 6). These models estimate the odds that a workplace is a more intensive computer technology implementer (using the categories first introduced in Table 3) given a number of characteristics. Training indicators—based on training expenditures per employee—are also included as control variables, since training may be a substitute for employee education (even though most evidence indicates it is actually complementary). The results are most easily interpreted in terms of odds ratios. For example, an odds ratio of 1.05 for education in Model 1 indicates that each increase in the average level of workforce education is associated with a five percent increase in the odds that the workplace is at a higher level of computer technology investment (Table 6, Model 1, first row). Similarly, odds ratios for categorical variables such as "low training" are interpreted relative to an omitted *reference category*—in this case workplaces who did no formal training (the odds ratios are the bracketed numbers in Table 6). So workplaces that spent between $1 and $199 per employee on training in 1999 (the low training group) were 47% more likely to be at a higher level of computer spending than workplaces who spent nothing on employee training (the reference category).

These regressions reiterate the finding that workplaces whose employees are better educated are more likely to introduce a new technology and to spend more per employee on that hardware/software implementation. The relationship between education and technology implementation remains significant when training, workplace size, industry, region, and individual level controls are added (Models 3 to 6). The existence of separate education and training effects indicates that training is not a perfect substitution for employees' education level.

Although the coefficient for education appears small relative to training effects, it is important to remember that the education variable in these models was entered as a 28-level semi-continuous variable, so that each increment in education is quite small and the estimation procedure assumes a constant incremental effect across all levels of education. On this scale, for example, 9 increments separate a grade 12 education from a Bachelors degree so that there is quite a large difference in the probability of implementing (about 45%) between a hypothetical workplace employing only high school graduates and one that employs only university graduates. In fact, the literature suggests that there may be "threshold effects" between education and technology: some increments in education may have a stronger association with technology than others.

A university education is frequently cited as just such a threshold in the association between technology and education. To test for this effect, the logit models were rerun using a dichotomous variable for education that distinguishes those with at least some university education from those who have none (Table 7)[3]. The results do indicate the presence of a strong threshold effect for university education: employers with university-educated employees are more likely to invest (or invest more) in hardware/software than employers without university-educated employees. Although the effect of university-educated employees is diminished somewhat with the addition of controls for training, workplace size, industry and region,

[3] We tested specifications where education was classified into six ordinal categories. The university indicator was the only level of education that had a consistently significant coefficient.

Table 7

Employers' hardware/software investments related to employees' university education
Log odds and odds ratios (parentheses) from ordered logit models

Selected variables	Model 1 education	Model 2 training	Model 3 education, training	Model 4 education, training, size	Model 5 = Model 4 + industry, region	Model 6 = Model 5 + experience, gender, age
University education	.40*** (1.49)		.36** (1.43)	.35** (1.42)	.29* (1.33)	.29* (1.34)
Low training		.38* (1.47)	.40* (1.49)	.38* (1.46)	.35* (1.42)	.35* (1.42)
Medium training		1.00*** (2.72)	.99*** (2.68)	.97*** (2.62)	.87*** (2.39)	.87*** (2.39)
High training		.79*** (2.20)	.75*** (2.12)	.74*** (2.09)	.47* (1.61)	.47* (1.61)

* p <.05; ** p < .01; *** p < .001
Reference category for education is *post-secondary education or less*.

it none-the-less remains strong and statistically significant. For example, in the most complete models, workplaces with university-educated employees are much more likely to invest (or invest more) in computer technology than other workplaces.[4]

The results in this section demonstrate a clear association between an employer's investment in computer technology and the education of its workforce—more intensive technology investors generally have more highly educated employees. More specifically, there appears to be a clear threshold in the relationship between computer investment and employees' education: workplaces with at least some university educated employees tend to invest more in computer hardware/software. This association coexists with the relationship between computer technology and computer-related training described in the previous section.

[4] We also tested a model that allowed education to have a different effect for workplaces with varying levels of training – mainly to see if the combination of university educated employees and high levels of training resulted in an extra technology boost (i.e. a multiplicative rather than an additive effect). These interaction terms were separately and jointly insignificant.

Are Highly Educated Workers More Likely to Be Found in Implementing Workplaces?

In the previous section, the analysis focused on workplaces. They were identified by their intensity of hardware/software implementations and the analytical techniques highlighted differences in the distribution of education at various levels of computing investment, while accounting for other workplace and individual characteristics. In this section the focus is on the individual, particularly whether individuals holding jobs in workplaces that invest heavily in computer-based technologies have higher levels of education than employees in other workplaces. This is an alternative view on the same relationship that was examined in the previous section and can be viewed as corroborating evidence. As before, education is defined in several alternative forms: semi-continuous (28 levels), ordinal (6 levels) and binary (2 levels). The alternative education variables require different forms of regression analysis, but the results are very consistent across the models.

Using the semi-continuous education variable, we first fit Ordinary Least Square (OLS) models on hardware/software implementation costs per employee, training, and other controls (Table 8). Looking at the regression equivalent of a simple cross-tabulation, Model 1 indicates that working for an employer who spent $2,500 or more per employee on new hardware/software and, to a lesser extent, an employer who spent from $1-$699 per employee was associated with significantly higher levels of education.

Table 8

Employees' education related to employer hardware/software investments

OLS models[1]

	Model 1 H/S implementation	Model 2 = Model 1 + gender, age, experience	Model 3 = Model 2 + industry, region, size	Model 4 = Model 3 + training costs (employer)	Model 5 = Model 4 + employee computer training	Model 6 = Model 4 + 1 year employee training
H/S Implementation – Low <$699	.43* (.21)	.44* (.21)	.12 (.17)	.09 (.17)	.06 (.17)	.07 (.16)
H/S Implementation – Medium $700-$2,499	.19 (.29)	.22 (.28)	-.06 (.24)	-.11 (.25)	-.16 (.24)	-.13 (.24)
H/S Implementation – High $2,500+	1.22*** (.27)	1.26*** (.26)	.89*** (.34)	.86*** (.23)	.80** (.23)	.82*** (.23)
Training–low (employer)				0.4 (.16)	.00 (.16)	-.09 (.16)
Training–medium (employer)				.21 (.18)	.15 (.18)	.02 (.17)
Training–high (employer)				.39 (.21)	.32 (.21)	.19 (.20)
Employee trained in last 12 months						.97*** (.11)
R squared (unadjusted)	.0060	.0157	.1624	.1633	.1696	.1765
Adjusted Wald (Implementation)	p < .001	p < .001	p < .001	p < .001	p < .001	p < .001

1 These models were estimated with STATA procedures that provide a good approximation of the workplace sample design effects, but do not account for the second stage sampling of employees. As such, the significance of the results of Model 6 were verified using a custom application that accounts for design effects, post-stratification and second-stage sampling.

* p < .05; ** p < .01; *** p < .001

Standard errors in parentheses.

Source: Workplace and Employee Survey 1999.

Although the addition of individual controls for gender, age and experience (Model 2) has almost no effect on these results, the association began to weaken (becoming insignificant for the \$1-\$699 per capita group) when workplace-level controls for number of employees, industry and region were included (Model 3). However, the significant association between education and intensive computer technology implementation (\$2,500 or more per employee) persists in all models, including additional controls for workplace and employee-specific training.

The training variables produced some interesting results in and of themselves (Models 4 to 6). Interestingly, workplace per-employee spending on training is not significantly related to employee education even though coefficients are in the expected direction.[5] On the other hand, employee-specific training (that is training undertaken by the survey respondents) was positively and significantly related to the employee's level of education. This result was noted both for computer-specific training and other forms of training. So better-educated employees are more-or-less randomly distributed across workplaces with varying levels of employee training, but are more likely to receive training than less-educated employees within all types of establishments.

Since OLS regression rests on some strong assumptions about the variable of interest that were clearly not present in the semi-continuous education variable[6], the results were tested for robustness using two different measures of education—an ordinal measure and the dichotomous measure for university education—with corresponding estimation techniques.

5 The lack of precision in the relationship between employee education and workplace training expenditures may be a function of the data quality of the latter: training expenditure information could not be provided by approximately one-quarter of the surveyed workplaces.

6 Most notably, the education variable was not normally distributed with equal increments between levels of the variable.

In the first alternative, education is classified into six categories: less than grade 9; grades 9-13 (no diploma); high school diploma; non-university post-secondary; some university; and, university degree. This categorical variable is fit to the same independent variables as the OLS models using ordered logit models (Table 9). As with the OLS regressions, only very intensive levels of computer technology investment ($2,500 or more per employee) were consistently associated with significantly higher levels of employee education. The magnitude of the association was diminished by the addition of workplace controls for industry, region and size, but remained significant.

In the previous section, we entertained the notion that a university education (signalling that a person has “learned how to learn”) may be the only educational step that is really important to technology implementing employers. As such, we used logistic regression to fit a simple indicator of university education on the same sets of variables as the OLS and ordered logit models (Table 10). Here again the same pattern was evident: a university education was significantly associated with the highest level of hardware/software investment, the magnitude decreased with the addition of workplace-level controls, yet it remained significant.

These analyses indicate that highly-educated employees are more likely to work in workplaces that have spent $2,500 or more per employee to implement a hardware and/or software innovation in the past year. We also found that employees with higher levels of education were not concentrated in intensive-training workplaces, but rather that highly educated employees were more likely to receive training in all types of workplaces. Overall then, this section supports previous literature that better educated employees receive more training and work in more technologically-oriented workplaces. Moreover, workplaces with highly

Table 9

Employees' education related to employer hardware/software investments
Log odds and odds ratios (parentheses) from ordered logit models

	Model 1 H/S implementation	Model 2 = Model 1 + gender, age, experience	Model 3 = Model 2 + industry, region, size	Model 4 = Mode l 3 + training costs (employer)	Model 5 = Model 4 + employee computer training	Model 6 = Model 4 + 1 year employee training
H/S Implementation – Low <$699	.17 (1.18)	.20 (1.22)	.06 (1.06)	.04 (1.04)	.03 (1.03)	.04 (1.04)
H/S Implementation – Medium $700-$2499	.04 (1.04)	.06 (1.06)	-.07 (.93)	-.09 (.91)	-.11 (.90)	-.10 (.90)
H/S Implementation – High $2500+	.48*** (1.62)	.50*** (1.65)	.39** (1.48)	.37** (1.45)	.35** (1.42)	.36** (1.43)
Adjusted Wald (Implementation)	p < .001	p < .001	p < .001	p < .001	p < .001	p < .001

p < .05; ** p < .01; *** p < .001.
Source: Workplace and Employee Survey 1999.

Table 10

Employees' university education related to employer hardware/software investments

Log odds and odds ratios (parentheses) from ordered logit models

	Model 1 H/S implementation	Model 2 = Model 1 + gender, age, experience	Model 3 = Model 2 + industry, region, size	Model 4 = Mode l 3 + training costs (employer)	Model 5 = Model 4 + employee computer training	Model 6 = Model 4 + 1 year employee training
H/S Implementation – Low <$699	.20 (1.22)	.20 (1.22)	.09 (1.09)	.08 (1.08)	.07 (1.07)	.07 (1.07)
H/S Implementation – Medium $700-$2,499	.03 (1.03)	.04 (1.04)	-.07 (.93)	-.09 (.91)	-.10 (.90)	-.09 (.91)
H/S Implementation – High $2,500+	.50*** (1.65)	.51*** (1.66)	.40** (1.49)	.39** (1.48)	.37** (1.45)	.38** (1.46)
Adjusted wald (Implementation)	p < .001	p < .001	p < .05	p < .05	p < .05	p < .05

* p < .05; ** p < .01; *** p < .001.

Source: Workplace and Employee Survey 1999.

educated workers are more likely to implement new computer technologies than other workplaces. However, there are a couple of caveats to keep in mind. Education and technology implementation, according to the WES data, are associated mainly at a high threshold of technology spending that only a relatively small proportion of workplaces attain. It is also important to remember that cross-sectional models do not indicate the direction of causation—there is likely a synergistic or reinforcing relationship between the technological capacity of a workplace and the education level of its workforce.

Are Recent Hires Better Educated than the Current Stock of Employees?

The previous sections examined whether the current stock of employees of technology-implementing workplaces had higher levels of education than the current stock of employees in non-implementing workplaces. Note that this essentially draws a comparison between a stock on the one hand (employees' education) and a flow (incremental investment in computer technology) on the other. However, it seems likely that recently hired employees may better reflect the labour demand effects of recent technology implementation. As such, this section focuses on employees hired in approximately the same 12-month period in which the computer technologies in question were implemented. Specifically, we add a variable identifying employees hired in the 12 months prior to the survey to the regression models outlined in the previous sections and interact it with the implementation variables to test:

1. whether new employees of hardware/software implementers have higher levels of education than current employees and,
2. whether new employees of hardware/software implementers have higher levels of education than new employees of other workplaces.

Although the focus on new employees would seem to stand on firmer theoretical ground than the previously presented results, there are several factors that potentially cloud the findings. First, the sample size of newly hired employees is much smaller than the overall employee sample, which will tend to reduce the precision of estimates for this sub-population.

Furthermore, low-wage, low-skill jobs tend to turn over at a much higher rate than high-skill jobs which could mask the education-technology relationship if labour demand is segmented within businesses. Third, the analyses do not take into account intra-year timing issues—specifically whether hiring preceded or followed the reported implementation(s)[7].

There are two components to address in determining whether new hires in computer-implementing workplaces are better educated than the existing stock of employees. The first is to determine whether this relationship, in fact, exists. Secondly, the effect should either be absent or substantially weaker in non-implementing workplaces. Both of these conditions are borne out in the results, albeit with some imprecision in the measurement.

As mentioned earlier, both an indicator of new hires and interactions between this variable and the computer spending indicators were added to models outlined in the previous section. In this formulation, the coefficient of the new hire indicator (Table 11, column 1) represents the relative education of new hires in non-implementing establishments. The results from all three models are clear: new hires in non-implementing workplaces have no more education than their longer-tenured colleagues. On the other hand, the implementation-new hire interaction term (Table 11, column 2) indicates that new hires are better educated than their co-workers within implementing workplaces. The coefficients for the

[7] Although the survey contains the information to define new hires in relation to the timing of the hardware and/or software implementations there are several factors that would limit the accuracy of such a measure: differing reference periods (employees were typically interviewed 3-4 months after their employers) recall error (which increases after six months) and item non-response by either the employer or employee. Furthermore, employers may well change hiring priorities in anticipation of a major technological implementation.

logistic and/ordered logistic models indicate appreciable and significant effects. A randomly selected new employee in an implementing workplace is at least one-third more likely to be at a higher level of education than their longer tenured co-workers. The coefficient for the OLS model is similar in magnitude, but is not significant at the customary level of .05. Therefore, all else equal, newly hired employees in implementing workplaces are more likely than their co-workers to have a university degree (logistic model) or more generally to be found among the higher rungs of the six-level education scale outlined earlier (ordered logisitic model).

We also looked at separate interactions between the new hire variable and the indicators of increasing computer investment per employee to determine if new hires had relatively higher levels of education (relative to their co-workers) as the level of computer technology investment intensified (columns 3 to 5 in Table 11). The results indicate a significant effect for workplaces that invested less than $700 per employee, no significant effect at the middle level of technology investment and a relatively large effect among the most intensive technology implementers that was only significant in the ordered logistic model. Note that new employees of the most intensive implementers are twice as likely to have a university education as employees of non-implementers. We have no intuition on the "J" pattern outlined by these coefficients (i.e. appreciable effect, no effect, large effect), but suspect it may result from measurement imprecision related to the one-year horizon on computer technology investments and the relatively small number of both workplaces and new employees at the higher levels of investment.

We turn now to the comparison between new employees of implementing versus non-implementing workplaces. The interaction terms

Table 11
Are new hires in hardware/software(H/S) implementing workplaces better educated than current employees?

Type of regression	New hire in-non-implementers 1	New hire + new hire x H/S 2	New hire + new hire x H/S low 3	New hire + new hire x H/S med 4	New hire + new hire x H/S high 5
OLS	-.34	.39	.59*	-.50	1.16
(Standard error)	(.22)	(1.53)	(.32)	(.43)	(.72)
Logistic	-.10	.36*	.52**	-.31	.73
(Odds ratio)	(.90)	(1.43)	(1.68)	(.73)	(2.07)
Ordered logistic	-.17	.29*	.34*	-.09	.81*
(Odds ratio)	(.84)	(1.34)	(1.40)	(.91)	(2.24)

* $p < .05$; ** $p < .01$; *** $p < .001$.
Source: Workplace and Employee Survey 1999.

between the new-hire indicator and the hardware-software implementation variables are direct tests of the hypothesis that new hires of computer technology implementers are better educated than new hires in other workplaces. The results of the regression models generally confirm this hypothesis although some of the estimates again suffer from a lack of precision. Comparing all computer technology implementers to non-implementers (Table 12, column 1), the OLS, ordered logistic and logistic models all indicate significant educational differences among new hires that extend across the schooling spectrum. The odds ratios indicate that a randomly selected new hire in an implementing workplace is more than half-again as likely to be at a higher level of education than a randomly selected new hire in a non-implementer.

If the education level of new hires is related to hardware/software implementation then one would expect their relative education (compared to new hires of non-implementers) to increase with the intensity of computer technology investments. Here the results are mixed. In each of the models, the largest interaction coefficient corresponds to the highest

Table 12

Are new hires in hardware/software (H/S) implementing workplaces better educated than new hires in non-implementing workplaces?

Type of regression	New hire x H/S 1	New hire x H/S low 2	New hire x H/S med 3	New hire x H/S high 4
OLS	.78*	.93*	-.16	1.5*
(Standard error)	(2.21)	(.38)	(.47)	(.75)
Logistic	.46*	.63**	-.21	.84
(odds ratio)	(1.58)	(1.88)	(.81)	(2.31)
Ordered logistic	.47**	.52**	.08	.98*
(odds ratio)	(1.60)	(1.68)	(1.08)	(2.66)

* p < .05; ** p < .01; *** p < .001.
Source: Workplace and Employee Survey 1999.

per employee implementation investment although the coefficient in the logistic model is not significant (Table 12, columns 2, 3 and 4). Smaller, but more precise, coefficients are noted for implementers that spent less than $700 per employee on computer technologies (column 2). Again the results for middle level of computer investment ($700-$2,499 per employee) are puzzling: the education of their new hires does not differ significantly from new hires in non-implementers and is significantly less than the education level of new hires of more and less intense technology implementers.

In summary, we find that new employees of computer technology implementers are generally better educated than both their longer-tenured peers within implementing workplaces and new hires of non-implementing workplaces. Although the education differentials do not rise monotonically with increasing intensity of computer technology investment, this may be an artefact of measurement imprecision. On balance, then, we find reasonably robust micro-level evidence that investments in computer technology are associated with a simultaneous increase in the demand for more highly educated workers.

Conclusion

The skill-biased technological change hypothesis is grounded in the notion that the increasing prevalence of computer technology is increasing the demand for highly skilled (educated) labour relative to lesser skilled (educated) labour. The hypothesis has most frequently been examined with industry-level data or, less frequently, plant-level data from the manufacturing sector. However, when plant-level data are encountered in the literature, employee skill is typically proxied by the ratio of white-collar to blue-collar workers. Similarly, if household survey data are used to get better indicators of employee education or skills then industry-level technology indicators are the norm. The main contribution of this study is that it has combined workplace-level technology information with information on the education and training of employees within those workplaces.

The 1999 Workplace and Employee Survey provides detailed information on major hardware and software implementations in the 12 months leading up to April 1999 (along with a wide range of other information) for workplaces across a broad range of industries. It also contains detailed information on the computer use, computer training, other types of training and education of a sample of employees within each of those workplaces. This study combined data from those employers and employees to add some new observations concerning the micro-level foundations of the skill-biased technological change hypothesis. The main findings are:

1. **Major implementations of computer hardware and/or software are associated with elevated rates of computer-related training.** At first blush this finding seems patently obvious: employees need to learn how to use new hardware and software systems. However, it also indicates that new systems require skills that are scarce, at least for some period, within individual workplaces—this is one of the foundations of the skill-biased technological change hypothesis. Furthermore, since computer hardware and software systems have relatively short life cycles, the need for new training should recur frequently. Thus technology-intensive employers may well favour employees who possess the educational credentials that demonstrate they have learned how to learn.
2. **From the workplace perspective, employers with university-educated employees are more likely to invest in computer technology implementations.** Although we did find evidence of a weak linear relationship between per employee computer investment and a semi-continuous education variable, the evidence was strongest for a step effect associated with the presence of university-educated employees. This finding adds support to the notion that technology-intensive employers would place a premium on hiring employees who have the educational signals that they will be effective learners—a notion that is very suggestive of skill-biased technological change.
3. **From the employee perspective, university-educated workers are more likely to be found in the most technology-intensive workplaces.** The employee models did not find a linear relationship between education level and the employer's computer technology spending. Instead, there was an educational step effect

associated with employers that spent $2,500 or more per employee on computer hardware and software. These models also added an interesting twist to the training story: highly educated workers were not unduly concentrated in high-training workplaces, but they were more likely to receive training than their less-educated co-workers, regardless of the overall training level of the workplace.

4. **New employees of computer technology implementers are better educated than their longer-tenured co-workers.** This is an important addition to the evidence base on skill-biased technological change since it relates marginal change in computer technology to marginal change in the intra-establishment distribution of education. Although it could be argued that this is simply a consequence of the increasing average level of education of the workforce, our findings indicate otherwise. First, new hires in non-implementing workplaces are no better educated than their co-workers. Second, new hires in implementing workplaces are significantly better educated than new employees of non-implementing establishments. Thus the concentrated hiring of highly educated workers within implementing establishments clearly seems to be a demand-generated phenomenon.

It is also important to restate some of the caveats associated with these results. Although the WES will eventually provide longitudinal data, these results pertain only to the first cross section. Thus they cannot yet provide information on the long-term trends outlined by the skill-biased technological *change* hypothesis. Moreover, the information on computer technology investments is probably quite noisy in comparison to the accumulated technological capacity in the sampled workplaces. This undoubtedly affected the precision of some of our results. We expect that the longitudinal data, as they become available, will provide the basis to both refine and expand these findings particularly with respect to the direction of causation.

Perhaps the most interesting line of inquiry will be to examine wages within the framework of the skill-biased technological change hypothesis. Remember that the hypothesis emerged as a broad-stroke explanation for increasing returns to education in the United States. Yet the relative returns to higher education in Canada and most European countries have remained much more stable. The hypothesis would also seem to imply that a wage premium should exist for on-the-job computer use. However, most recent studies have found little or no computer wage premium after controlling for unobserved heterogeneity. It seems likely that WES information such as the type of computer applications used and the revealed ability to train oneself to perform new computing tasks, not to mention workplace technology investments, could provide interesting new insights into these issues.

Appendix A: Concepts and Methods

Objectives

The Workplace and Employee Survey (WES) is designed to explore a broad range of issues relating to employers and their employees. The survey aims to shed light on the relationships among competitiveness, innovation, technology use and human resource management on the employer side and technology use, training, job stability and earnings on the employee side.

The survey is unique in that employers and employees are linked at the micro data level; employees are selected from within sampled workplaces. Thus, information from both the supply and demand sides of the labour market is available to enrich studies on either side of the market.

Sample sizes and response rates

WES was conducted for the first time during the summer (employer survey part) and fall of 1999 (employee survey part). Just over 6,350 workplaces and about 24,600 employees responded to the survey, representing response rates of 94% and 83%, respectively. The employer sample is longitudinal—the sampled locations will be followed over time, with the periodic addition of samples of new locations to maintain a representative cross section. Employees will be followed for two years only, due to the difficulty of integrating new employers into the location sample as workers change companies. As such, fresh samples of employees will be drawn on every second survey occasion (i.e. first, third, fifth). This longitudinal aspect will allow researchers to study both employer and employee outcomes over time in the evolving workplace.

Appendix A–Table 1. Sample sizes and estimated populations

Industry/Workplace size/Region	Workplaces		Employment	
	Number of respondents	Estimated population	Number of respondents	Estimated population
Overall	**6,351**	**735,911**	**24,597**	**10,777,543**
Industry				
Forestry, mining, oil and gas extraction	313	13,359	1,193	190,453
Labour intensive tertiary manufacturing	406	20,584	1,620	497,409
Primary product manufacturing	318	7,648	1,434	392,872
Secondary product manufacturing	292	11,762	1,191	371,888
Capital intensive tertiary manufacturing	359	17,059	1,469	585,253
Construction	607	54,659	2,095	419,373
Transportation, warehousing, wholesale trade	706	84,820	2,877	1,114,182
Communication and other utilities	413	9,712	1,376	243,601
Retail trade and consumer services	515	249,409	1,864	2,596,439
Finance and insurance	498	34,153	1,893	512,159
Real estate, rental and leasing operations	364	24,429	1,143	189,303
Business services	467	83,245	1,830	1,006,460
Education and health services	751	109,404	3,193	2,340,519
Information and cultural industries	342	15,669	1,419	317,632
Workplace size				
1-19 employees	2,872	640,077	6,154	3,471,168
20-99 employees	1,743	83,412	8,356	3,260,557
100-499 employees	1,249	10,735	6,810	1,960,109
500 employees or more	487	1,687	3,277	2,085,708
Region				
Atlantic	777	63,152	3,003	709,303
Quebec	1,432	153,277	5,745	2,560,682
Ontario	1,626	276,920	6,187	4,352,265
Manitoba	423	27,888	1,641	402,138
Saskatchewan	329	29,333	1,217	322,333
Alberta	839	80,063	3,183	1,076,019
British Columbia	925	105,279	3,621	1,354,803

Source: Workplace and Employee Survey, 1999.

Appendix A–Table 2. Response rates

Category	Employer response rate (%)	Employee response rate (%)
Overall	**94.0**	**83.1**
Industry		
Forestry, mining, oil and gas extraction	97.0	87.1
Labour intensive tertiary manufacturing	91.0	81.3
Primary product manufacturing	95.3	85.7
Secondary product manufacturing	94.7	85.7
Capital intensive tertiary manufacturing	94.5	84.4
Construction	94.3	83.8
Transportation, warehousing, wholesale trade	92.6	84.5
Communication and other utilities	98.0	82.9
Retail trade and consumer services	93.3	82.2
Finance and insurance	96.5	87.5
Real estate, rental and leasing operations	97.3	87.8
Business services	94.2	85.7
Education and health services	96.8	86.5
Information and cultural industries	98.1	87.9
Workplace size		
1-19 employees	96.9	85.0
20-99 employees	95.1	86.8
100-499 employees	92.4	85.0
500 employees or more	93.4	81.6
Region		
Atlantic	96.3	88.8
Quebec	92.4	82.5
Ontario	95.6	84.2
Manitoba	96.4	87.7
Saskatchewan	96.7	86.3
Alberta	94.9	85.0
British Columbia	96.2	85.1

Source: Workplace and Employee Survey, 1999.

Target population

The target population for the employer component is defined as all business locations operating in Canada that have paid employees, with the following exceptions:

a) Employers in Yukon, Northwest Territories and Nunavut
b) Employers operating in crop production and animal production; fishing, hunting and trapping; private households and public administration.

The target population for the employee component is all employees working in the selected workplaces who receive a Customs Canada and Revenue Agency T-4 Supplementary form. If a person receives a T-4 slip from two different workplaces, then the person will be counted as two employees on the WES frame.

Survey population

The survey population is the collection of all units for which the survey can realistically provide information. The survey population may differ from the target population due to operational difficulties in identifying all the units that belong to the target population.

WES draws its sample from the Business Register (BR) maintained by the Business Register Division of Statistics Canada, and from lists of employees provided by the surveyed employers.

The Business Register is a list of all businesses in Canada, and is updated each month using data from various surveys, profiling of businesses and administrative sources.

Reference period

The reference period for WES is mainly the 12-month period ending March 1999. Some questions in the workplace portion covered the last pay period ending before March 1999.

Sample design

The survey frame is a list of all units that carries contact and classification (e.g., industrial classification) information on the units. This list is used for sample design and selection; ultimately, it provides contact information for the selected units.

i) Workplace survey

The survey frame for the workplace component of WES was created from the information available on the Statistics Canada Business Register.

Prior to sample selection, the business locations on the frame were stratified into relatively homogeneous groups called *strata*, which were then used for sample allocation and selection. The WES frame was stratified by industry (14), region (6), and size (3), which was defined using estimated employment. The size stratum boundaries were typically different for each industry/region combination. The cut-off points defining a particular size stratum were computed using a model-based approach. The sample was selected using Neyman allocation. This process generated 252 strata with 9,144 sampled business locations.

All sampled units were assigned a sampling weight (a raising factor attached to each sampled unit to obtain estimates for the population from a sample). For example, if two units were selected at random and with equal probability out of a population of ten units, then each selected unit would represent five units in the population, and it would have a sampling weight of five.

The inaugural WES survey collected data from 6,351 out of the 9,144 sampled employers. The remaining employers were a combination of workplaces determined to be either out-of-business, seasonally inactive, holding companies, or out-of-scope. The majority of non-respondents were owner-operators with no paid help and in possession of a payroll deduction account.

ii) Employee survey

The frame for the employee component of WES was based on lists of employees made available to interviewers by the selected workplaces. A maximum of twelve employees was sampled using a probability mechanism. In workplaces with fewer than four employees, all employees were selected.

Data collection

Data collection, data capture, preliminary editing and follow-up of non-respondents were all done in Statistics Canada Regional Offices. Interviewers in person collected the workplace survey data. The workplace questionnaire covered a wide range of topics. For about 20% of the surveyed units (mostly large workplaces), more than one respondent was required to complete the questionnaire. For the employee component, telephone interviews were conducted with persons who had agreed to participate in the survey by filling out and mailing in an employee participation form.

Statistical edit and imputation

Following collection, all data were analyzed extensively. Extreme values were listed for manual inspection in order of priority determined by the size of the deviation from average behaviour and the size of their contribution to the overall estimate.

Respondents who opted not to participate in the survey—*total non-response*—were removed and the weights of the remaining units were adjusted upward to preserve the representativity of the sample. For respondents who did not provide all required fields—*item non-response*—a statistical technique called *imputation* was used to fill in the missing values for both employers and employees. The particular method that was selected for this purpose, *weighted hot-deck*, is based on first identifying respondents at a certain level called *imputation class*, and then from within the imputation class a donor is selected using a probability mechanism. The donor's value is then transferred to the missing field of the non-respondent.

The WES components were treated independently even if some questions on the employee questionnaire could have been imputed from the related workplace questionnaire.

Estimation

The reported (or imputed) values for each workplace and employee in the sample are multiplied by the weight for that workplace or employee; these weighted values are summed up to produce estimates. An initial weight equal to the inverse of the original probability of selection is assigned to each unit. To calculate variance estimates, the initial survey weights are adjusted to force the estimated totals in each industry/region group to agree with the known population totals. These adjusted weights are then used in forming estimates of means or totals of variables collected by the survey.

Variables for which population totals are known are called auxiliary variables. They are used to calibrate survey estimates to increase their precision. Each business location is calibrated to known population totals at the industry/region level. The auxiliary variable used for WES is total employment obtained from the Survey of Employment, Payrolls and Hours.

Estimates are computed for many domains of interest such as industry and region.

Data quality

Any survey is subject to errors. While considerable effort is made to ensure a high standard throughout all survey operations, the resulting estimates are inevitably subject to a certain degree of error. Errors can arise due to the use of a sample instead of a complete census, from mistakes made by respondents or interviewers during the collection of data, from errors made in keying in the data, from imputation of a consistent but not necessarily correct value, or from other sources.

Sampling errors

The true sampling error is unknown; however, it can be estimated from the sample itself by using a statistical measure called the *standard error*. When the standard error is expressed as a percent of the estimate, it is known as the relative standard error or *coefficient of variation*.

Non-sampling errors

Some non-sampling errors will cancel out over many observations, but systematically occurring errors (i.e. those that do not tend to cancel) will contribute to a bias in the estimates. For example, if respondents consistently tend to underestimate their sales, then the resulting estimate of the total sales will be below the true population total. Such a bias is not reflected in the estimates of standard error. As the sample size increases, the sampling error decreases. However, this is not necessarily true for the non-sampling error.

Coverage errors

Coverage errors arise when the survey frame does not adequately cover the target population. As a result, certain units belonging to the target population are either excluded (under-coverage), or counted more than once (over-coverage). In addition, out-of-scope units may be present on the survey frame (over-coverage).

Response errors

Response errors occur when a respondent provides incorrect information due to misinterpretation of the survey questions or lack of correct information, gives wrong information by mistake, or is reluctant to disclose the correct information. Gross response errors are likely to be caught during editing, but others may simply go through undetected.

Non-response errors

Non-response errors can occur when a respondent does not respond at all (total non-response) or responds only to some questions (partial non-response). These errors can have a serious impact on estimates if the non-respondents are systematically different from the respondents in survey characteristics and/or the non-response rate is high.

Processing errors

Errors that occur during the processing of data represent another component of the non-sampling error. Processing errors can arise during data capture, coding, editing, imputation, outlier treatment and other types of data handling. A coding error occurs when a field is coded erroneously because of misinterpretation of coding procedures or bad judgement. A data capture error occurs when data are misinterpreted or keyed in incorrectly.

Joint interpretation of measures of error

The measure of non-response error and the coefficient of variation must be considered jointly to assess the quality of the estimates. The lower the coefficient of variation and the higher the response fraction, the better will be the published estimate.

Confidentiality

The information presented in this publication has been reviewed to ensure that the confidentiality of individual responses is respected. Any estimate that could reveal the identity of a specific respondent is declared confidential, and consequently not published.

Response/non-response

a) ***Response rate:*** includes all units, which responded by providing "usable information" during the collection phase.

b) ***Refusal rate:*** includes those units, which were contacted but refused to participate in the survey.

Appendix B – Construction of Education Variables

The education variable was created from the following questions.

Q47. What is the highest grade of elementary high school (secondary school) that you have completed? Please report the highest grade, not the year when it was completed.

Q48. Did you graduate from high school (secondary school)? (responses: yes, no)

Q49. Have you received any other education? (responses: yes, no)

If yes,

Q50. What was that education (Check all that apply.)

- ❑ Trade or vocational diploma or certificate
- ❑ Some college, CEGEP, institue of technology or nursing school
- ❑ Completed College, CEGEP, institute of technology or nursing school
- ❑ Some university
- ❑ Teachers’ college
- ❑ University certificate or diploma below bachelor level

- ❑ Bachelor or undergraduate degree or teachers' college (e.g. B.A., B.Sc., B.A.Sc, 4-year B.Ed.)
- ❑ University certificate or diploma above bachelor level
- ❑ Master's degree (M.A., M.Sc., M.Ed., MBA, MPA and equivalent)
- ❑ 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., M.DIV.) or 1-year B.Ed. after another bachelor's degree
- ❑ Earned Doctorate
- ❑ Other industry certified training or certification courses
- ❑ Other, specify __________________.

To create the education variable, respondents who reported not graduating high school AND not pursuing post-secondary education except industry training or other were coded according to their highest level of education completed up to grade 13 (categories 0-13). Respondents who graduated high school but had no post-secondary education except industry certification or other were coded 14. Respondents who reported receiving post-secondary education were assigned the highest category that they reported, according to the order in the table below. This includes those who answered no to whether they graduated from high school.

Estimated Population Distribution of Education Variable (N = 24,002)

Category	Value	Weighted N
None	0	2,590
Grade 1	1	597
Grade 2	2	2,543
Grade 3	3	8,383
Grade 4	4	13,209
Grade 5	5	20,406
Grade 6	6	28,862
Grade 7	7	49,836
Grade 8	8	104,459
Grade 9	9	100,558
Grade 10	10	339,131
Grade 11	11	397,460
Grade 12	12	160,498
Grade 13	13	21,343
High school diploma but no post-secondary	14	2,139,341
Trade/Vocational	15	922,031
Some college, no trade/vocational	16	1,028,707
Some college + trade/vocational	17	57,829
Completed college	18	1,833,656
Some university	19	782,837
Teachers college	20	26,441
Univ. certificate less than bachelors	21	180,071
Bachelors degree, no teacher's college or certificate less than bachelors	22	1,230,337
Bachelors + univ. cert. below bachelors	23	42,524
Univ. cert. above bachelors	24	191,903
Master's degree	25	341,648
Medical, law, theology degree	26	81,763
Ph.D.	27	58,769

Source: *Workplace and Employee Survey, 1999.*

Note: An ordinal variable for education was created by collapsing this classification into the six categories shown in the following table.

Estimated Population Distribution of Categorical Education Variable

Categories	Value	Weighted N
Primary education only – grade 8 or less	1	230,884
High school education – no diploma or post-secondary education	2	1,018,990
High school diploma – no post-secondary education	3	2,139,341
Non-university post-secondary education	4	3,842,223
University education less than bachelor's degree	5	989,349
Bachelor's degree and above	6	1,946,943

Source: Workplace and Employee Survey, 1999.

Appendix C. Industry and Region Characteristics

Hardware/Software Technology Implementation, by Industry (N = 6,346)

Industry	Implemented any hardware/ software technology (as % of all who implemented	Implemented any hardware/ software technology (as % of industry	3-digits north American industry classification system (NAICS)
Forestry, mining, oil, and gas extraction	1.69	21.94	113, 115, 211, 212, 213
Labour intensive tertiary manufacturing	3.01	25.31	311, 312, 313, 314, 315, 316, 337, 339
Primary product manufacturing	1.16	26.13	321, 322, 324, 327, 331
Secondary product manufacturing	1.55	22.86	325, 326, 332
Capital intensive tertiary manufacturing	3.13	31.74	323, 333, 334, 335, 336
Construction	5.09	16.10	231, 232
Transportation, warehousing, wholesale	15.42	31.44	411, 412, 413, 414, 415, 416, 417, 418, 419, 481, 482, 483, 484, 485, 486, 487, 488, 493
Communication and other utilities	1.24	22.08	221, 491, 492, 562
Retail trade and consumer services	21.19	14.70	441, 442, 443, 444, 445, 446, 447, 448, 451, 452, 453, 454, 713, 721, 722, 811, 812
Finance and insurance	8.61	43.62	521, 522, 523, 524, 526
Real estate, rental and leasing operations	3.17	22.41	531, 532
Business services	17.67	36.72	533, 541, 551, 561
Education and health services	13.70	21.67	611, 621, 622, 623, 624, 813
Information and cultural industries	3.36	37.11	511, 512, 513, 514, 711, 712
Total	99.99	Mean = 23.51	

Source: Workplace and Employee Survey, 1999.

Hardware/Software Technology Implementation, by Region (N = 6,346)

	Percent of all hardware/software implementers	Percent of region's businesses implementing hardware/software
Atlantic	7.37	20.18
Quebec	20.32	22.93
Ontario	41.07	25.66
Prairies	7.23	21.85
Alberta	11.15	24.09
British Columbia	12.86	21.13
Total	100.00	Mean = 23.51

Source: Workplace and Employee Survey, 1999.

Appendix D

Table 1. Detailed Results of Training Regresssion

Independent variables	Training logit
Hardware/software implementation cost/employee	
$0 (omitted)	
$1-$699	0.93***
$700-$2,499	1.27***
$2,500+	0.84***
Proportion of computer users in the establishment	2.06***
Number of competitors	
0 to 5 competitors in principal market (omitted)	
6 to 19 competitors in principal market	0.51**
20 or more competitors in principal market	0.51**
Number of employees	
1 to 19 employees (omitted)	
20 to 99 employees	1.49***
100 to 499 employees	2.05***
500 or more employees	3.07***
Industry	
Forestry (omitted)	
Mining and oil and gas extraction	0.45
Utilities	0.08
Construction	0.63
Manufacturing	-0.59
Wholesale trade	0.01
Retail trade	0.30
Transportation and warehousing	-0.38
Information and cultural industries	0.33
Finance and insurance	0.84**
Real estate and rental and leasing	-0.59
Professional, scientific and technical services	-0.35
Management of companies and enterprises	1.13

Table 1. Detailed Results of Training Regresssion – Concluded

Independent Variables	Training Logit
Industry	
Admin. support, waste management and remediation services	-0.50
Educational services	-0.42
Health care and social assistance	-0.25
Arts, entertainment and recreation	-1.87*
Accommodation, food and other services (ex. public admin.)	0.38
Proportion of professionals in workplace	
0 professionals (omitted)	
>0 to 10% professionals	0.98***
>10%, <=25% professionals	1.21***
Greater than 25% professionals	0.31
Proportion of employees covered by a collective bargaining agreement (CBA)	
0 employees covered by a CBA (omitted)	
>0 to 50% covered by CBA	0.25
>50% to 90% covered by CBA	0.76**
More than 90% covered by a CBA	1.16**
Unemployment rate in economic region	-2.00
Constant	-3.17***
Hardware/software implementation cost/employee > $0	1.01***

Based on 5,246 observations.

Note: The training model was fit using a binary logistic model on the probability that computer-related formal or informal training was offered by the employer in the period March 1998 to March 1999.

* Significant at the .1 level.

** Significant at the .05 level.

*** Significant at the .01 level.

Source: Workplace and Employee Survey, 1999.

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