The Link between Technology Use, Human Capital, Productivity and Wages: Firm-level Evidence

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THE MARKED INCREASE IN COMPUTER USE, and more generally the use of information and communication technologies (ICT), is widely acknowledged as the major change to have occurred in the workplace over the past decade. Growth in real investment in computers in Canada averaged a phenomenal 30 per cent per year between 1989 and 2000, and that in all ICT goods was 17 per cent per year over the same period. By 2000, ICT investment as a whole represented nearly one-third of total business investment in machinery and equipment in Canada.

The increase in ICT investment in Canada was followed by an acceleration in labour productivity growth in the latter part of the 1990s. Annual labour productivity growth in the business sector was more than a full percentage point higher during the 1996-2000 period than it was between 1989 and 1996. The adoption of new technologies coincided with growing needs in human capital over this period, reflecting the complementarity between these two forms of investment in the production process.

Despite the general acceptance of a relationship between technology, human capital and productivity, few firm-level studies have been conducted to empirically evaluate the productivity gains associated with the use of these technologies in Canada. Furthermore, micro-level economic studies have not been able to directly examine the way in which the combination of investments in technology and human capital affects the productivity of firms and the wages of workers, mostly reflecting the lack of data on both firm and employee characteristics. This article summarizes research based on a relatively new Canadian database, the 1999 *Workplace and Employee Survey* (WES), which links data on Canadian employees and employers, to help fill this research gap.

We address three research questions. First, we examine how the use of technology is related to the level of productivity in Canadian firms, controlling for a number of firm- and worker-specific characteristics. Second, we investigate whether the productivity benefits are indeed greater when technology use is combined with

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investments in human capital such as education and training. This allows us to ask the policy question of whether firm-provided training can successfully adjust the qualifications of lower-skilled workers and make firms equally well-off in terms of their productivity. Third, we examine to what extent the gains in productivity associated with ICT and human capital are reflected in better wages for workers. To empirically investigate these issues, we simultaneously estimate production and earnings functions and then compare relative wages and relative productivity for various groups of workers.

It should be stressed at the outset that this research is based on a cross-section of data for one year only, which restricts our focus to determinants of productivity levels rather than growth. Studies using future waves of the WES data will be able to determine whether technology use and human capital also enable firms to achieve future productivity gains, or whether other characteristics play a bigger role in generating increases in productivity. In this regard, the WES provides an exciting new source of data for Canada, and this study represents an important first step.

Survey of empirical research

ICT use and productivity

There have been few studies on the relationship between technology use and productivity at the firm level in Canada, and those that have been done have focused on the number of technologies adopted and have been limited to the manufacturing sector (Baldwin and Sabourin, 2004). Ideally we would like to differentiate firms that make intensive use of ICT from those in which ICT use is limited. We also want to include the service sector in the analysis, as this sector accounted for over 80 per cent of ICT investment in Canada over the 1989 to 2000 period. The use of the WES helps fill this research gap, as it covers both the manufacturing and non-manufacturing sectors, and includes data on the intensity of technology use within them.

Human capital and productivity

On the education front, there is no shortage of empirical evidence that education and worker wages are positively correlated.[2] Using linked worker-employer datasets, several U.S. studies have also found a positive link between productivity levels and workforce education at the firm level (Black and Lynch, 1996 and 2000).

Human capital includes not only the education workers bring to the job, but also skills learned while working and adapting to new technologies. There is quite a large and varied empirical literature on the effect of training on productivity and wages at the firm level. Even though several studies have concluded that investments in training have a significant positive effect on the level and the growth of productivity at the firm level, particularly structured training (provided outside of the workplace), others have shown that these gains are a function of the type of training provided (Black and Lynch, 1996; Dearden, Reed and Van Reenen, 2000; and Barrett and O'Connell, 2001). In particular, Black and Lynch (1996) show that only training related to computers has a positive effect on the productivity of non-manufacturing firms. For Canada, existing research on the impact of investment in training on productivity has been largely qualitative.[3]

2 See Card (1999) for a detailed review of literature on the wage gains associated with education.

3 To our knowledge, the only study that measures the gains in productivity resulting from investment in training is that of Betcherman, Leckie and McMullen (1997). The researchers showed that firms that were highly committed to training were more likely to report an upward trend in productivity between 1993 and 1995 than those that did not offer training. However, in this case productivity was measured based on subjective evaluations from employers.

Studies suggest that the productivity gains associated with training are twice as high as the wage gains.[4] In a competitive job market, we would expect that the differences in productivity resulting from the investments in human capital would be entirely reflected in wage differentials. However, in practice, the relationship between gains in productivity and wages can vary according to the origin of the financing, the nature of the human capital acquired, and job market structure, among other factors. In the case of training, it is probable that there is a considerable divergence between wages and productivity gains since employers bear part of the costs of training. Thus, unlike education, the wage premium associated with training is likely to constitute a lower bound of productivity gains resulting from this investment.

Education, training and technology use: Complementary investments?

Clearly investments in education, training and new technologies are closely related. Training plays a significant role when technological change is rapid and the knowledge necessary to implement the new technologies is very specific. For example, a number of studies have established that the implementation of new technologies in Canadian manufacturing firms increased the level of required qualifications and stimulated firms to invest in training (e.g. Baldwin and Peters, 2001 and Baldwin, Gray and Johnson, 1997).

Canadian and U.S. research has also shown that highly educated workers are more likely to participate in training than those with little education, suggesting a complementary relationship between human capital acquired through the education system and that acquired through in-house training (Bartel and Sicherman, 1998; Lynch, 1992; and Leonard, Montmarquette and Turcotte, 2003). This finding may be cause for some concern as workers with less education may have difficulties meeting the rising skill demands of the workplace. However, U.S. research has found that the participation differentials in training between workers with little education and those who are highly educated are mitigated to some extent (although not eliminated) when there is a high rate of technological change. To our knowledge there has been no study investigating this link in Canada. Our study fills this gap.

Determinants of firm-level productivity in Canada

Characteristics of firms in the Workplace and Employee Survey

We use the 1999 Workplace and Employee Survey (WES), a survey developed by Statistics Canada and Human Resource Development Canada. The WES is the first data set that allows an analysis of the effects of both human capital and technology use on productivity of Canadian firms. We link the WES employee file (24,597 employees) to the employer file (6,351 locations) and include only for-profit locations with more than one employee interviewed, leaving us with a final sample of 4,219 locations for which we have average employee characteristics. About 84 per cent of locations have less than 20 employees, with an average for our entire sample of 16 employees per location.[5] The sample is primarily composed of domestic-owned locations, with only about 6.5 per cent of locations foreign-owned (i.e., more than 50 per cent of assets controlled by foreign interests).

4 Dearden, Reed and Van Reenen (2000) used sectoral data for England to show that an increase of 5 per cent in the proportion of employees trained had the effect of increasing hourly wages by 2 per cent and productivity by 4 per cent.

5 The survey covers locations, which is not a true measure of firms (several locations can be part of the same firm). However, for simplicity, we use the terms interchangeably.

On average, only about a third of workers per location have completed post-secondary education – 23 per cent with a college diploma and just over 13 per cent with a university degree. Almost 15 per cent on average in a location have not completed high school, while the remaining 50 per cent attained at most a high school diploma, trade designation or some post-secondary schooling (without completion).

On average, 24 per cent of employees in a location received training in the reference year of the WES (April 1998 to March 1999). On average, only 12 per cent of employees in a location received computer training, yet 54 per cent of employees in a location use computers on the job.

Using data available from the survey, we define productivity as value added per worker, where value added is measured as gross revenues minus expenses on materials. Expenses on materials are equal to gross operating expenditures less payroll and expenses on non-wage benefits and training.

Before turning to an empirical analysis, we start by drawing observations from the raw data. Table 1 presents summary statistics of key variables according to whether locations are in a "high-productivity" or "low-productivity" group (locations have been statistically sorted into one of two groups according to their level of productivity). Toward assessing the complementarity of technology use and human capital, we also create a set of interaction terms between workers who use a computer and their education and training characteristics and report them in Table 1. The following insights emerge:

- As expected, a much larger share of employees in high-productivity locations have a university degree, and a much smaller share have less than a high school diploma. There is little difference between the two clusters for other education levels. Generally speaking, training variables and technology use rise with the level of education attained.
- High-productivity locations provide more training to employees. There is a much larger differential between low- and high-productivity firms in terms of computer training on hardware/software (whether formal or informal) than for the other types of training (professional training, team-building, or other types). Only 8.5 per cent of employees in low-productivity locations received training on computers, compared to 18.5 per cent in the high-productivity cluster.
- Computer use is much more prevalent among employees in the high-productivity location cluster (66 per cent versus 47 per cent in the low-productivity cluster), although the same is not true for other forms of technology use. There is no statistical difference between the share of workers using computer-controlled technologies in low- and high-productivity clusters, and using "other types of technology" (including devices such as fax machines) is more common among employees in low-productivity firms. Thus, the raw data suggest that there is something unique about computer use for productivity.
- Among the 54 per cent of workers in our sample using a computer, a large proportion do not have a university degree and had not participated in computer training in the WES reference year. Only a small proportion of employees in a location satisfied all three criteria; however, the share of workers with these characteristics is more than five times higher in high-productivity locations. Regression analysis will allow us to determine whether the combination of these characteristics makes a large difference to productivity, as well as give us information on the extent to which training compensates for education.

Turning to other firm characteristics, a few points of interest arise. High-productivity firms

Table 1

Selected Descriptive Statistics

	Mean		
	All	Low productivity	High productivity
Education, training, techology use ***(% of employees)***			
Less than high school diploma	0.147	0.168	0.113
High school diploma, trade vocational course or industry certified	0.319	0.332	0.309
Some college degree or university	0.177	0.183	0.172
Completed college and university below bachelor degree	0.228	0.220	0.239
University degree completed	0.134	0.100	0.177
Bachelor degree	0.096	0.073	0.120
Advanced degree	0.038	0.027	0.056
Share of workers trained in "classroom"	0.236	0.200	0.295
Share of workers trained "on the job"	0.241	0.234	0.265
Share of workers who took training on software/hardware	0.121	0.085	0.185
Share of workers who took classroom training on software/hardware	0.053	0.036	0.080
Share of workers who took on-the-job training on software/hardware	0.077	0.053	0.119
Share of workers who took a professional training	0.138	0.142	0.138
Share of workers who took a training on team-building	0.012	0.013	0.011
Share of workers who took any other types of training	0.168	0.170	0.171
Share of workers using a computer	0.539	0.469	0.662
Share of managers using a computer	0.119	0.106	0.137
Share of non-management workers using a computer	0.420	0.363	0.525
Share of workers using computer-controlled technologies	0.119	0.112	0.125
Share of workers using any other types of technologies	0.331	0.373	0.267
Share of workers not using a PC	0.461	0.531	0.338
Share of workers using a PC, without univ. and without training on PC	0.346	0.328	0.393
Share of workers using a PC, without univ. and with training on PC	0.083	0.064	0.119
Share of workers using a PC, without univ. and trained in classroom on PC	0.038	0.028	0.055
Share of workers using a PC, without univ. and trained on-the-job on PC	0.052	0.040	0.073
Share of workers using a PC, with univ. and without training on PC	0.080	0.067	0.090
Share of workers using a PC, with univ. and with training on PC	0.030	0.011	0.060
Share of workers using a PC, with univ. and trained in classroom on PC	0.011	0.004	0.023
Share of workers using a PC, with univ. and trained on-the-job on PC	0.021	0.008	0.042
Firm Characteristics (% of locations)			
Inward-oriented domestic firms	0.902	0.925	0.866
Outward-oriented domestic firms	0.033	0.023	0.046
Foreign-owned firms	0.065	0.052	0.089
Profit-sharing compensation	0.091	0.056	0.145
R&D is a high priority	0.234	0.202	0.286

Note: There are 4,219 locations in our sample. The sample is resticted to for-profit locations where at least two employees were surveyed. The low- and high- productivity clusters are generated using the FASTCLUS procedure in SAS.

are more likely to claim that research and development (R&D) is a high priority in their location. A profit-sharing compensation scheme is offered in 15 per cent of high-productivity firms, compared to only 6 per cent of low-productivity firms. We also examine other compensation schemes such as individual incentive systems (bonuses, piece rates), group productivity gain sharing, or merit-based pay, but find little evidence that these other schemes are as linked to productivity in the raw data as profit-sharing. Finally, foreign ownership is more common in the high-productivity cluster, as are domestic firms with an outward orientation (i.e. those that sell a larger share of their sales to the international marketplace than to the national marketplace). It can be argued that firms participating in export markets and faced with international competition are driven to make productivity-enhancing investments or management changes to be successful, regardless of ownership.

Empirical results

In order to sort out the most important determinants of productivity, controlling for a wide variety of firm and worker characteristics, we turn to an econometric analysis. We estimate productivity and wage equations, in which the dependent variables are value added per worker and the total wage bill per worker respectively, and the explanatory and control variables include production variables (capital and labour);[6] share of workers with a university degree; share of workers trained, by type of training (computer, professional, team-building); share of workers using technology, by type of technology use (computers, computer-controlled technologies, other); workforce characteristics such as type of employment arrangement, gender, experience and occupation; firm characteristics such as trade orientation, foreign ownership, multi-location, collective bargaining agreement, age, average length of job tenure, R&D importance, and profit-sharing; industry controls; and regional controls. The equations are estimated jointly using nonlinear least squares to enable us to take into account the potential causality of productivity and wages and to compare the relative marginal productivities and wages for various groups of workers and firms using Wald tests on the equality of the parameters. In the regression analysis each observation is weighted by its WES employer-linked survey weight.

Table 2 presents the key estimation results for the productivity and wage equations. The estimates reported in the first column confirm the insights from the raw data: productivity is higher the more intensely technology is used within the firm (the higher the share of workers using a computer), the higher the share of workers with a university degree, the higher the share of workers participating in formal training, and the higher the share of workers receiving computer training. The estimates reported in column 2 provide the productivity return once we control for the other factors that affect productivity described above.

In most cases, the productivity return to the firm in Table 2 differs from the wage return to the worker. However, Wald tests on the equality of the estimated coefficients show that, in all but one case, the pair-wise coefficients from the two regressions are statistically equal, supporting the standard microeconomic assumption that workers are paid according to their marginal products.

6 Hours worked are not available in the WES, so the number of workers is used as the measure of labour input. We proxy the capital-labour ratio by the average level of capital per location in the industry (calculated by dividing non-residential capital stock data for 1998 from Statistics Canada by the survey-weighted number of locations in each industry, making the implicit assumption that total capital in an industry is evenly distributed across all locations in that industry) divided by the number of workers in the location. This procedure will likely over-estimate the capital in small locations and under-estimate the capital in large locations. We do not expect these distortions between large and small firms to be meaningful as most locations in our sample are small.

Table 2
Location-level value added and earnings functions

	(A) Value added function		(B) Earnings function	
	Without controls	With controls	Without controls	With controls
	(1)	(2)	(3)	(4)
Technology use				
Share of workers using computers	0.502***	0.286**	0.353***	0.187***
Education				
% with University degree	0.192*	0.209*	0.167**	0.128**
Training				
Share of workers trained on-the-job	-0.046	-0.035	-0.069	-0.036
Share of workers trained in class	0.355**	0.121	0.306***	0.077
With computer training	0.478***	0.450**	0.176*	0.121
Firm Characteristics				
Outward-oriented domestic	—	0.333***	—	0.207***
Employee turnover	—	-0.076*	—	-0.043*
Profit-sharing compensation	—	0.209**	—	0.128***
R&D is a high priority	—	0.046	—	0.047*
Sample Size	4,219	3,863	4,447	4,070
R-squared	0.139	0.287	0.200	0.498

Note: Equations are jointly estimated using nonlinear least squares for the purposes of the Wald tests of equality of the productivity and wage parameters. Dependent variables: (A) log value added per worker; (B) log wage bill per worker. Each estimation includes the production variables, firm-level and employee-level characteristics and controls for industry and region. R-squared and sample size based on individual regressions. Significance (p-value under a t-test): ***1% level; **5% level; *10% level.

As discussed below, the one case for which this is not true is the case of computer training.

Technology use

The estimated impact of a 10 percentage point increase in computer use on productivity in column 1 of Table 2 is 5 per cent. The productivity premium falls to 2.9 per cent when we include the industry controls, reflecting the fact that the relatively more productive locations in our sample are concentrated in industries that have a high intensity of ICT-use, such as wholesale trade, finance, insurance and real estate, business services, and information services. Among the four most ICT-intensive industries to which locations in our sample are classified, ICT investment increased by a combined 57 per cent over the period 1995-1999 according to national data.[7]

Human capital

The link between education and the level of productivity is robust, with a 10 percentage point increase in the share of workers with a university degree generating a productivity return of about 2 per cent, both with and without the control variables. However, formal (structured or in class) training becomes insignificant at the 10 per cent level in both the productivity and wage equations when we control for other factors. While previous research has generally found a large and significant productivity return to structured training, it is important to recognize that we only measure training in the current year. To the extent that new skills take time to be reflected in productivity, the insignificance of the general on-the-job and in class training variables is perhaps not surprising. Nevertheless,

7 Based on unpublished data from Statistics Canada.

consistent with the findings of Black and Lynch (1996), the coefficient on computer training remains a highly significant determinant of firm productivity. The results show that a 10 percentage point increase in the share of workers receiving computer training is associated with 4.5 per cent higher productivity. This supports the view that it is not so much the quantity of training provided, but the subject matter of that training that matters for productivity.[8]

Moreover, when we disaggregate computer training into on-the-job versus formal classroom training on computers, we find that computer skills development on the job is responsible for the productivity gains.[9] A potential explanation for the significance of computer training on the job but not general on-the-job training (for a given year of training) is that this type of training can be put to use more quickly than other forms, reducing the lag required to see the benefits. It also may capture some unobserved ability, as those most likely to learn computer skills on the job have a higher aptitude for learning in general. As in the unconditional regression, the productivity return to firms is much larger than the wage return to workers in the case of computer training, consistent with the empirical literature (Dearden, Reed and Van Reenen, 2000). Moreover, in contrast to the other pair-wise coefficients in the two regressions, this difference is statistically significant. That is, the 4.5 per cent increase in productivity associated with a 10 percentage point increase in the share of workers receiving computer training is statistically higher than the increase in wages (1.2 per cent, albeit insignificant at the 10 per cent level).

Other determinants of productivity

As suggested by the raw data, the use of a profit-sharing compensation scheme is associated with higher productivity and higher wages. Consistent with other evidence for Canada (Baldwin and Gu, 2003), the results suggest that trade orientation is more important for firm productivity than ownership per se. The productivity of a location that is domestic but outward-oriented is 40 per cent higher than that of its inward-focused counterpart.[10] Although the actual number of these domestic-owned "global" locations is relatively small in our sample, these firms realize large and significant productivity gains compared to locations that focus mostly on the local or national market. Workers in these firms also earn higher wages.

We also find that while locations that place a high priority on R&D have higher productivity in the raw data, this is no longer statistically significant once we control for other factors. Similarly, Baldwin and Sabourin (2004) show that investments in R&D are associated with higher market share but not higher labour productivity in Canadian manufacturing. This may reflect the fact that R&D in Canada tends to be focused on developing new products rather than new processes.

Sectoral and firm size differences

Estimating the equations by major sector, we find that education and technology use are important determinants of productivity in both the manufacturing and non-manufacturing sectors; however, we find that the impact of training differs. Our finding that an increase in the

8 Arguably, the statistical insignificance of the general training variables may also be related to the sampling errors imposed by using the employee data at the employer level. However, when we compare results from employee and employer information for the training and computer use variables (for which we have information from both sources), we find no substantial difference in the results.

9 See the unabridged version of this paper for the results for disaggregated computer training.

10 The outward orientation variable is binary, and its estimated coefficient from the second column of Table 2 is 0.333. The marginal effect of a change from zero to one of this variable (inward orientation to outward orientation) can be approximated as $e^{0.333}$-1=40 per cent.

Table 3
Interactions between human capital and technology use

	(A) Value added function		(B) Earnings function	
	Without controls	With controls	Without controls	With controls
	(1)	(2)	(3)	(4)
Share of workers with university degree	0.524*	0.507*	-0.070	-0.067
Share of workers trained	-0.057	-0.157	0.061	-0.011
Share of workers using a PC and with:				
Non-university degree and no training on PC	0.445***	0.253**	0.340***	0.172***
Non-university degree and training on PC	1.060***	0.754***	0.632***	0.286***
University degree and no training on PC	0.110	-0.155	0.736***	0.406**
University degree and training on PC	0.844**	0.695**	0.923***	0.643***
Sample Size	4,219	3,863	4,447	4,070
R-squared	0.122	0.284	0.176	0.498

Note: Individual regression results using linear least squares. Dependent variables: (A) log value added per worker; (B) log wage bill per worker. Each estimation includes the production variables, firm-level and employee-level characteristics and controls for industry and region. Significance (p-value under a t-test): ***1% level; **5% level; *10% level. Results by university education and the type of computer training (on-the-job training versus classroom training) can be found by consulting the unabridged version of this article.

share of computer skills training has a significant impact on productivity is driven by the non-manufacturing sector: we do not find a significant relationship between an increase in computer training and productivity in the manufacturing sector. Our results show that only education and computer use have positive and significant effects on location-level productivity in this sector.

The effects of human capital and technology use also differ by location size. Employing a higher share of workers with a university degree is found to be more important in locations with less than 20 employees than in larger locations, and the same is true for computer use. Larger locations, in contrast, realize a larger productivity benefit from a higher share of workers receiving formal training.

The positive link between productivity and outward orientation (i.e. selling a larger share of products or services to the international market than to the national market) holds in both the manufacturing and non-manufacturing sectors.

The interaction between human capital and technology use and the effect on productivity

Using worker interaction terms (based on combinations of computer users and their education and training characteristics), in addition to the individual control variables for education and training, and the same production and control variables used in the previous regressions, we re-estimate the productivity and wage equations.

The results are presented in columns (2) and (4) of Table 3. As expected, the productivity results confirm that the largest productivity gains accrue to locations that combine technology, education and learning. Controlling for the share of workers with a university degree, we see there is an additional productivity gain for locations that have a larger share of university-educated workers who also use a computer and participate in computer training. A 10 percentage point increase in the share of workers with all three characteristics is associated with 7 per cent higher productivity, in addition to the gain from an increase in the share of university workers alone.

Of particular interest, we find a large productivity gain from an increase in the share of computer users who do not have a university degree but participate in computer training. A 10 percentage point increase in the share of this type of worker yields 8 per cent higher productivity. This suggests that computer skills training can augment the qualifications of lower-skilled workers and make firms equally well-off in terms of the productivity gain associated with technology use. While firms still exhibit higher productivity with a higher share of workers with a university degree, there is nevertheless a productivity gain associated with a higher share of non-university-educated workers using technology as long as they receive computer skills development.

As noted earlier, our analysis at the aggregate level suggests that the productivity-enhancing aspect of computer training reflects on-the-job training. Thus we also separate the computer training variable according to whether the employee participated in classroom or on-the-job training. The results show that an increase in the share of university-educated workers using a computer and participating in classroom training does not have a significant impact on productivity (over and above the benefit solely from that associated with education alone). In contrast, for an increase in computer users who do not have a university degree but receive computer training, the productivity gain comes both from classroom and on-the-job training. This suggests that workers without post-secondary education also benefit from a more structured learning environment to realize the productivity benefits associated with technology use than those with a university degree.

Generally speaking, we find that technology-users, regardless of their particular technology-skill mix, receive some wage premium over workers that do not use a computer and this return increases with the level of human capital.

Conclusion

This paper examines the effects of education, training and technology use on productivity and wages at the firm level in Canada, using a new linked employee-employer data set. To a growing empirical literature on micro-level analysis of the determinants of productivity, our analysis contributes cross-sectional evidence for Canada that computer use, university education and computer skills development are associated with higher productivity. It contributes to the existing literature for Canada by measuring the impact of the intensity of technology use on productivity for the economy as a whole, rather than just technology adoption at the manufacturing level as in previous studies.

A number of our findings have interesting policy implications relating to productivity. We find evidence that computer skills training can augment the qualifications of lower-skilled workers and make firms equally well-off in terms of the productivity gain associated with technology use. The productivity benefit associated with computer use is enhanced by a higher share of workers receiving computer training regardless of whether or not they have a university degree. However, the type of computer training that raises productivity for university-educated technology users is learned on the job, while both on-the-job and structured classroom computer training matter in the case of non-university educated workers. As well, our study supports the view that export orientation matters for productivity. Domestic firms that are global in nature, measured here as those who sell the largest share of their products or services to an international market, have higher productivity on average than domestic firms who sell primarily to their local or national market.

By quantifying the productivity benefit associated with the use of technology and human capital and testing the relationship between productivity and wages for different groups of workers, our study makes an important contribution to a growing body of firm-level research in Canada. However, this is just a first step. In this study we have only been able to discover what factors are associated with higher productivity levels. Ideally we would like to discover what factors actually cause higher productivity levels, as well as the factors that cause higher productivity growth. The availability of data for more than one year would obviously allow us to analyze productivity growth, since growth rates could be calculated based on level estimates in each year.

Data for other years would also allow us to address the issue of causality. It may be that locations with high productivity levels are simply locations that are more likely than low-productivity locations to use advanced technologies, employ educated workers, enter the export market and train their employees, rather than these factors actually causing higher productivity levels. Indeed, several studies (e.g. McGuckin, Streitwieser and Doms, 1998) have shown that results based on cross-sectional data are not supported when unobserved location-specific effects are taken into account. Multiple years of data would allow us to undertake panel regression analysis and control for these location-specific fixed effects.

Fortunately, WES is a longitudinal survey for Canada, and therefore we will be able to address these issues in a more dynamic setting in the future. Moreover, additional years of data will also help overcome the measurement issues surrounding the training variable, incorporating the fact that the productivity benefits of some types of training may occur with a lag. This will allow for a better estimate of the return to training than what we can achieve with one year of data.

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