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Productivity and Wages: Measuring the Effect of Human Capital and Technology Use from Linked Employer-Employee Data

by

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Abstract

The use of information and communication technologies and investment in education and training are widely believed to play an important role in productivity growth at the aggregate level. However, a lack of micro-level data with information on firms and their workforce has limited the extent to which technology use and human capital could be linked to productivity at the firm level. This paper attempts to fill this research gap, using a new Canadian survey of both establishments and their workers -- the 1999 Workplace and Employer Survey. We examine the relationship between education, training, and technology use and firm productivity and wages, controlling for various firm and worker characteristics (including industry, foreign ownership, trade orientation, employee turnover, experience, occupation, etc.). We find strong evidence that computer use, university education and computer skills development are associated with higher productivity and higher wages. Moreover, the productivity benefit associated with computer use is enhanced when more workers receive computer training, regardless of whether or not they have a university degree.

Résumé

L’utilisation des technologies de l’information et l’investissement en éducation et formation sont largement reconnus comme des éléments clés de la croissance de la productivité au niveau agrégé. Toutefois, le manque de base de données contenant de l’information tant sur les emplacements que sur les employés a limité l’ampleur avec laquelle l’utilisation de technologies et le capital humain ont pu être liés à la productivité au niveau de l’entreprise. Ce papier tente de combler cette lacune en utilisant une nouvelle enquête canadienne reliant les établissements et leurs employés – l’Enquête de 1999 sur le Milieu de Travail et les Employés. Nous examinons les liens existants entre l’éducation, la formation et l’utilisation de technologie sur la productivité et les salaires, tout en contrôlant pour plusieurs caractéristiques de l’entreprise et des travailleurs (incluant le secteur industriel, la présence d’intérêts étrangers, l’ouverture au commerce, le roulement des travailleurs, l’expérience, la répartition professionnelle, etc.). Nous obtenons une forte évidence selon laquelle l’utilisation d’ordinateurs, la scolarité de niveau universitaire et le développement de compétences liées à l’utilisation d’ordinateurs sont associés à une plus grande productivité et de meilleurs salaires. Nous montrons également que les gains de productivité liés à l’utilisation d’ordinateurs s’en trouvent accrus lorsque les travailleurs bénéficient de formation, et ce peu importe le niveau de scolarité des travailleurs.

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1. INTRODUCTION

"Productivity growth has benefited not only from an increase in the amount of capital per worker, especially of high-tech capital, but also from the enhanced efficiencies that have been made possible in combining labor and capital in the workplace."

Roger W. Ferguson, Vice Chairman Federal Reserve Board (July, 2001)

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 29 percent per year between 1990 and 2000. Globally, real investments in ICT[1] increased by 17 percent per year on average during the same period, accounting for nearly one third of total business investment in machinery and equipment.

The increase in ICT investment in Canada has been 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 1997–2000 period than it was between 1990 and 1996. The implementation of investments in new technologies also 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, no micro-level economic study has been able to directly examine the way in which the combination of investments in technology and human capital affects

[1] ICT is defined here as computers and office equipment, software and telecommunications equipment.

the productivity of firms and the wages of workers. This study uses a 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 major issues in this paper. First, we examine how the use of technology is related to the level of productivity in Canadian establishments controlling for a number of firm- and worker-specific characteristics such as industry, foreign ownership, trade orientation, employee turnover, average experience, and occupation distribution. Second, we investigate whether the productivity benefits are indeed greater when technology use is combined with 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. Lastly, we examine the extent to which the productivity premium associated with technology use and human capital investments is 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. As a result, our analysis can provide no information on the way in which technology and human capital affect changes in productivity over time. While this is a limitation, the study nevertheless provides useful information as a first step into a literature which is currently lacking for Canada. Our analysis allows us to quantify the productivity returns to firms from the use of technology and highly-skilled workers, both separately and in a number of different combinations. Studies using future waves of the WES data will allow us to determine whether these characteristics 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.

This paper is organized as follows. The second section provides a survey of the literature regarding the effect of technology use and human capital on productivity and wages. The third section describes the *Workplace and Employer Survey* and the underlying methodology in the econometric analysis. The data and empirical results of our analysis are presented and discussed in the fourth and fifth sections. The last section orients our results within the context of literature in this field and suggests avenues for future research.

2. A SURVEY OF EMPIRICAL RESEARCH

Several factors have been proposed to explain the productivity differentials between firms, such as more intensive use of capital (of new technologies in particular), organizational change, investment in research and development, trade orientation, and the use of more qualified employees, to name a few. Studies of the contribution of investments in new technologies and human capital have been limited in Canada, due mostly to a lack of data on these two characteristics at the firm-level. As a result, most of the literature we draw upon in this section regarding human capital and technology use is based on findings from other countries.

2.1 Information and communication technologies

A great number of studies have attributed a large part of the recent acceleration in U.S. labour productivity growth to efficiency gains achieved through increased production and use of ICTs. Oliner and Sichel (2000) estimate that half of the U.S. productivity growth acceleration between the first half and the second half of the 1990s was due to the use of ICTs, while ICT production accounted for another 25 percent. Stiroh (2001) confirmed these results on a sectoral level, illustrating that the sectors with the fastest rate of acceleration in labour productivity near the end of the

1990s were also the ones that had intensively used and produced ICTs at the beginning of the decade.

In Canada, empirical studies carried out at the aggregate level on productivity growth are not as conclusive. For instance, some studies have found that the contribution from the use of ICT to labour productivity growth remained constant between the first and second half of the 1990s (Harchaoui et al., 2002; Khan and Santos, 2002; Muir and Robidoux, 2001), suggesting that the observed gains stemmed from factors other than ICT. However, several U.S. studies (Brynjolfsson and Hitt 2000; Stiroh 2001) suggest that there is a significant delay between the adoption of new technologies and the corresponding productivity gains. For Canada, Baldwin and Sabourin (2001) find that manufacturing firms that adopted and combined several types of technologies (software, hardware, and network communication systems) by 1998 had greater productivity growth over the 1988-97 period. The end-of-period technology use is interpreted to be an indicator of the plant's ability to have learned how to integrate advanced technologies into the production process.

However, the data used by Baldwin and Sabourin (2001) only provide information on the number of technologies adopted at the plant-level, not the intensity of their use. Ideally we would like to differentiate firms that make intensive use of ICTs from those whose use is limited. McGuckin et al. (1998) find evidence that the positive relationship between productivity and advanced technologies is observed both in the number of technologies used and the intensity of their use. Black and Lynch (2000) found a strong positive relationship between the share of non-executive employees who used computers, a measure of the extent to which technology use is widespread throughout the organization, and the productivity of U.S. establishments.

Moreover, studies on ICT use in Canada such as that by Baldwin and Sabourin (2001) have been limited to the manufacturing sector. Yet the service sector has accounted for 84 percent of ICT investment in Canada over the course of the past decade. The present study helps fill this research gap, as our data set covers both the manufacturing and non-manufacturing sectors and the intensity of technology use within them (as measured by the share of workers using different types of technologies).

Empirical research has suggested that workers benefit from technology use in the form of higher wages. In the United States, it has been estimated that wage premiums vary between 8 percent and 15 percent according to the number and type of technologies used (Krueger, 1993; Dunne and Schmitz, 1995). Entorf and Kramarz (1997) estimated a wage premium to workers of 16 percent for the use of technologies that required a high level of autonomy (micro-computers, data entry, etc.). This premium could be further decomposed into 6 percent for workers with no experience in using ICT and 10 percent for workers with average experience. In Canada, Baldwin and Sabourin (2001) obtained similar wage advantage, varying between 6 percent and 11 percent for the most sophisticated manufacturing technologies.

2.1.1 The use of ICT and the wage premium: a causal relationship?

Recent empirical research has shown that the estimated wage premium on computer use in cross-sectional studies requires some care in interpretation. In their 1997 U.S. study, DiNardo and Pischke showed that the wage premium associated with the use of a pencil was almost as high as that associated with the use of a computer. Morissette and Drolet (1998) obtained similar findings for Canada by comparing the gains from computer use to those from using a fax machine. These findings suggest that the wage premium on computer use does not entirely reflect real productivity gains from computers, but that computer users possess a number of other unobserved, latent skills that affect their wages but cannot be controlled for in a cross-sectional analysis (DiNardo and Pischke, 1997). Entorf and Kramarz (1997) used a longitudinal database of French firms that controlled for latent skills and then evaluated the wage premium associated with the use of ICT. Their study showed that the initial wage premium of 6 percent for workers with no ICT experience became insignificant and the initial wage premium of 10 percent for skilled ITC workers fell substantially to 2 percent. The problem of causality has also been shown to affect productivity results to some extent. For example, McGuckin et al. (1998) show that the extent of technologies used and the intensity of their use are associated with higher firm productivity, but their productivity growth regressions show that the dominant explanation for the observed cross-sectional relationships is that good performers are more likely to use advanced technologies than poorly performing plants. While these micro-level findings are difficult to reconcile with the *aggregate-leve*l evidence (which shows that investment in ICT is making an important contribution to labour productivity growth in many countries), the empirical literature on causality is important to bear in mind as we interpret our cross-sectional results below.

2.2 Human capital: education and in-house training

We consider two types of investment in human capital in this study – the worker's highest level of educational attainment and the firm and worker's investment in in-house training. On the education front, there is no shortage of empirical evidence that education and productivity are positively correlated (using worker wages as a proxy for productivity).[3] Card (1999) provides a comprehensive review of the literature that suggests that one additional year of education is worth a wage increase in the order of 6 to 11 percent. Moreover, this premium is not substantially altered when the endogenous decision to become educated is modeled (e.g., from twin studies or natural experiments; see again Card, 1999). Using a linked data set, Black and Lynch (1996) show that an extra year of worker education increased productivity by 6 percent in U.S. non-manufacturing firms and by 5 percent in manufacturing firms. Jones (2001) found that education is positively correlated with wages and productivity in a sample of Ghanaian manufacturing firms and found that support for the theoretical claim that firms pay workers according to their productivity.

[3] See Card (1999), and Sianesi and Van Reenen (2002) for a detailed review of literature on the wage gains associated with education.

There is more to human capital than general education learned prior to employment. In-house training is considered to be a crucial ingredient to firm productivity and to employees' wage progression. For example, some specific skills involved in the operation of a business cannot be learned through the general learning framework provided by the education system. As well, many technological changes and new forms of work organization require workers to upgrade their skills on an ongoing basis, a task best accomplished through in-house training. See Box 1 for a discussion on the effect of training on wages according to human capital theory.

BOX 1 — Training and human capital theory

In human capital theory, training is viewed as an investment decision that increases productivity and thereby raises the wages of trainees by improving their skills and qualifications. In order to distribute the costs and benefits of training between firms and individuals, Becker (1964) distinguished training according to whether it was general (i.e. increasing productivity in the same way in all firms) or specific (i.e. increasing productivity only in the firm that provided training). In a perfectly competitive labour market, Becker (1964) showed that firms had no incentive to finance general training since they could not obtain an adequate return on investment by paying trainees below their marginal productivity. However, when training is purely specific, the costs and profitability of specific training will be shared between the workers and the firm.

Empirically, several studies (Barron, Black and Lowenstein 1989; Lynch 1992; Loewenstein and Spletzer 1998) have shown that the trained workers are not bearing the costs of general training by accepting initially lower wages. In fact, Loewenstein and Spletzer (1998) have shown that a large proportion of the explicit cost of general training is borne by the employer, who also partially benefits from the profits resulting from this training. Several theoretical works (Katz and Ziderman 1990; Stevens 1994; Loewenstein and Spletzer 1999; Acemoglu and Pischke 1999) have put forth some hypotheses supported by the Becker model in order to explain these empirical findings.

There is quite a large and varied empirical literature on the effect of training on firm's productivity and wages. Even though several studies have concluded that investments in training had a significant positive effect on the level and the growth of firm's productivity (Bartel 1989; Ballot et al 2001; Carriou and Jeger 1997), others have shown that these gains were a function of the type of training provided (Bishop 1994; Black and Lynch 1996; Dearden, Reed and Reenen 2000; Barrett and O'Connell 2001).

In general, training structured or provided outside of the workplace has been found to generate substantial and sustainable gains in productivity, whereas informal training or on-the-job training generated gains that were half as large, only during the first years of experience and with the employer who provided the training.[4] Black and Lynch (1996) showed that only training that is related to computers had a positive effect on the productivity of non-manufacturing U.S. firms.

In Canada, the only study that has measured 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.

Estimates of the wage premium associated with training vary between 5 percent and 15 percent in the U.S. (Barron, Black and Loewenstein, 1989; Altonji and Spletzer, 1991; Lynch, 1992; Veum, 1995; Veum, 1999). In Canada, Betcherman, Leckie and McMullen (1997) showed that participation in training was associated with a wage premium of 11 percent, based on a small sample of approximately 400 employees, representing 18 Canadian establishments. Although empirical findings on the return to training were initially similar to those obtained for education, the wage premium associated with training has been found to have diminishing returns. Frazis and Loewenstein (1999) show that the wage premium for the first 40 hours of training for

[4] Bishop (1994) showed that on-the-job training increased productivity by 9.5% percent with a current employer whereas training outside of the workplace increased productivity by 16 percent. Training outside of the workplace may also be more transferable since subsequent employers also remunerate this training.

a worker with little experience varies between 6 percent and 8 percent, a premium similar to one year of education. However, this premium reaches its maximum point two years after the participation in training and diminishes with the level of experience. Participation in training must be ongoing to preserve its beneficial effects.

Finally, some studies suggest that the productivity gains associated with training are twice as high as the wage gains. 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, job market structure etc. In the case of training, it is probable that there is a major 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. Dearden, Reed and Reenen (2000) used sectoral data for England to show that an increase of 5 percent in the proportion of employees trained had the effect of increasing hourly wages by 2 percent and productivity by 4 percent.

2.3 Education, in-house training and technology use: Complementary investments?

There are two widely known explanations for the link between human capital, productivity and wages: the human capital model described in Box 1 above, and Mincer's signalling theory, in which educated workers earn higher wages because educational attainment signals other positive qualities. A third explanation is that education improves workers’ ability to adjust more easily and quickly to the changes imposed by new technologies, thus returns to education may be higher in more dynamic or technologically-advanced environments (i.e., Jones, 2001). According to this view, the returns to education will not be the same for all workers with a given level of education.

Clearly investments in education, training and new technologies are closely related. The workforce education level can be viewed as a stimulant to the development and use of new technologies (Acemoglu, 1998). Training plays a significant role when technological change is rapid and the knowledge necessary to implement the new technologies is very specific. For example, numerous studies (Baldwin and Peters, 2001; Baldwin, Gray and Johnson, 1995 and 1997) 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. Likewise, in the U.S., Bartel and Sicherman (1998) showed that several technological change indicators positively influenced the number of hours of training through an increase in the participation of workers who had not received any previous training.

Bartel and Sicherman (1998) have shown that highly educated workers are more likely to participate in training than those with little education. This fact was confirmed by several other studies in the U.S. and Canada (Lowenstein and Spletzer, 1994; Lynch, 1992; Jennings, 1998; Leonard et al, 2003) and suggests a complementary relationship between human capital acquired through the education system and that acquired through in-house training. However, this finding may be cause for some concern as workers with little education may have difficulties meeting the rising skill demands of the workplace. Nonetheless, Bartel and Sicherman (1998) have pointed out 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) where there is a high rate of technological change.

To our knowledge there has been no study investigating the link between human capital, technology use, wages and productivity in Canada. Our study attempts to fill this gap.

3. ANALYTICAL FRAMEWORK

3.1 Production and Wage Function Estimates

(i) Productivity Differentials

The standard production model relates gross output to primary inputs (capital and labour), intermediate inputs (energy and materials), and total factor productivity as:

$$(1)\ Y_i = A_i f(K_i, L_i, M_i),\ i = firms$$

where Y is gross ouput, K is capital, L is hours worked, M is intermediate inputs, and A is total factor productivity. We could alternatively employ a value-added (V) concept for output that depends only on the primary input as:

$$(2)\ V_i = A_i f(K_i, L_i),\ i = firms$$

The empirical benefit of using the value-added specification is that it avoids the endogeneity problem in estimating the coefficient on materials (see Griliches and Ringstad (1971) and McGuckin et al (1998) for more details).[6] We use the value-added concept hereafter, but subsequent tests confirm that our results are similar using gross output.[7]

To estimate how different types of inputs affect labor productivity, we use a Cobb-Douglas production function. We extend the standard function to capture the productivity effects related to technology use ($Tech$), education ($Educ$), training ($Training$), as well as various firm characteristics (X_i) and workforce-employee composition (E_i). We define both inputs and outputs in per labour terms by dividing

[6] Ideally, we should have used lagged value of materials to avoid this problem. We will be able to address this issue more fully in the future as additional years of data are made available.
[7] Results not shown but available from the authors upon request.

through by L and relax the assumption of constant returns to scale by adding $\psi \ln L$. Taking natural logs yields the following productivity relationship:

(3)

$$\ln(LP_i) = a + \alpha \ln(K_i / L_i) + \psi \ln(L_i) + \beta_1 Tech_i + \beta_2 Educ_i + \beta_3 Training_i + \beta_4 X_i + \beta_5 E_i,$$

$i = \ firms$

where LP_i is total value-added per hours worked, a is a constant, α and ψ are the productivity elasticity of capital intensity and labour respectively, parameters β_j (j=1 to 5) measure productivity differentials according to the intensity of technology use, the share of educated workers, the share of workers trained, and different firm and worker characteristics, respectively.

We investigate the hypothesis that the more intensely technology is used within the firm, the more educated and the more trained is the workforce, the higher is firm-level productivity. This hypothesis is consistent with the view that new technologies contribute to productivity by enabling more efficient methods of processing information in many sectors of the economy while increases in human capital allow firms to capture the full benefits from using these new technologies.

Given that previous research suggests that investments in education, training and new technologies are complementary, we explicitly examine whether additional productivity gains accrue to locations that combine these forms of investments. We decompose the technology use variable in equation (3) into a series of interaction terms capturing the share of workers in each firm with a given combination of computer use, education and computer training characteristics. Specifically, equation (3) becomes:

(4) $$\ln(LP_i) = a + \alpha \ln(K_i / L_i) + \psi \ln(L_i) + \beta_1 TI_i + \beta_2 Educ_i + \beta_3 Training_i + \beta_4 X_i + \beta_5 E_i,$$

$i = \ firms$

where TI represents the vector of interaction terms on the technology use variable. Estimating equation (4) allows us to test the hypothesis that computer skills training may be able to compensate for university education, making the firm equally well-off in terms of its level of productivity.

Wage Differentials

Identifying the relationship between wages and marginal productivity is critical to understanding key labour market issues such as the returns to training and education, the causes of rising wages over the life cycle, and race and gender wage discrimination. The human capital theory in a perfectly competitive labour market predicts that wage differentials reflect differences in workers' marginal productivity. However, the recent availability of employee-employer linked data sets has allowed this assumption to be tested empirically, and recent evidence for the United States suggests that it may not hold in some cases. For example, for some demographic groups (i.e., women) lower wages are not reflected in actual lower relative marginal products (Hellerstein, Neumark and Troske, 1999). Also, when the cost of training is shared between employers and employees, the wage premium for training will underestimate the real return of training (Dearden, Reed and Reenen, 2000).

The wage equation can be written in a manner analogous to the productivity function above:

$$(5)\ \ln(WL_i) = \omega + \theta \ln(K_i / L_i) + \upsilon \ln(L_i) + \delta_1 Tech + \delta_2 Educ + \delta_3 Training + \delta_4 X_i + \delta_5 E_i\ ,$$
$$i = \ firms$$

where $\ln(WL_i)$ is equal to the logarithm of the total wage bill per hours worked, θ is the wage elasticity of capital intensity, υ is the wage elasticity of labour input, the parameters δ_k (k=1 to 5) measure wages differential according to the intensity of technology use, the share of educated workers, the share of workers trained, and different firm and worker characteristics, and the parameter ω is a constant. Similarly, the wage equation analogous to the productivity function with interaction terms is:

$$(6)\ \ln(WL_i) = a + \alpha \ln(K_i / L_i) + \psi \ln(L_i) + \beta_1 TI_i + \beta_2 Educ_i + \beta_3 Training_i + \beta_4 X_i + \beta_5 E_i,$$

$i = firms$.

The variables are defined the same as those in the previous section.

Estimation

As in Hellerstein, Neumark and Troske (1999), we jointly estimate the equations (3) and (5) using nonlinear least squares to enable us to take into account the potential causality of productivity and wages and to compare relative marginal productivity β_j and relative wages δ_k for various groups of workers and firms, using Wald tests on the equality of the parameters. We then estimate equation (3) and (5) by sector and firm size and conduct a robustness check on the results. Finally, we consider the effect of the interaction between education, training and technology use by estimating equation (4) and its wage-counterpart, equation (6) and use the Wald test for equality of the parameters.

3.2 The Workplace and Employee Survey

The analysis of the questions raised in the introduction requires a linked database providing information at the firm level as well as at the worker level. The data used in this research are from the Workplace and Employee Survey (WES), a survey developed by Statistics Canada and Human Resource Development Canada in 1999. This survey is unique for Canada in that it gathers detailed and linked data on business locations and their workers.[8] Employers were selected according to their geographical location and employees were then selected randomly from a list provided by the location.[9] The effective number of employees selected varied between 1 and 23 depending on the number of employees at the location, for an average of 5.5 employees surveyed per firm. WES is a longitudinal survey; it will be repeated for four years with the same locations and for two years with the same workers. The 1999 survey response rate was 95 percent

[8] It should be stressed that the survey covers locations, which is not a true measure of firms (several locations can be part of the same firm). However, for the sake of generality, we use the terms interchangeably in the paper.

for locations and 83 percent for employees; 6,351 locations and 24,597 employees answered the questionnaires. The use of calibrated survey weights gives a sample of locations and workers representative of the non-farm Canadian private sector.[10] The WES is essentially a survey of small firms – over 85 percent of the locations employ less than 20 employees.

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. On the employer side, the survey covers, among other things, sections on technology implementation, innovation, human resource practices, labour force turnover and business strategies. The use of new technologies, training participation (classroom or on-the job), types of compensation schemes, and conditions of employment are some of the sections covered by the employee questionnaire. Data normally collected in household surveys, such as age, sex, occupation, level of education, and tenure, for example, are also included in the WES database. Since one of the main purposes of our analysis is to look at the effect of human capital on productivity and wages, we must link the employee file to the employer file. The sample and data issues are discussed in more detail in the section below.

3.3 Sample and data issues

In order to use employee information on variables such as education, we link the WES employee file to the employer file using their location code. We restrict the sample to for-profit locations, for which more than one employee was interviewed at the particular location. This reduces our sample to approximately 5,200 locations. The sampling weights used for all estimation with the linked data take into account that we are using information on the average employee in each location.

Appendix 1 provides a detailed description of variables used in our analysis. Since hours worked are not available, the number of workers is used as the measure of labour input

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[9] The sample of locations was stratified by region, industry and size of the location.

[10] Locations in the Yukon, Nunavut and Northwest Territories were excluded, along with locations in the agriculture, fishing, and road, bridge and highway maintenance field, government services and religious organizations.

throughout. We define the dependent variable as the log of value-added per worker, where value added is measured as gross revenues minus expenses on materials.[11] We approximate expenses on material using gross operating expenditures minus payroll, expenses on non-wage benefits and training. We proxy the capital-labour ratio by the average level of capital per location in the industry divided by the number of workers in the location.[12] The average level of capital per location in the industry is calculated by dividing non-residential capital stock data for 1998 from Statistics Canada by the population-weighted number of locations in each industry, making the implicit assumption that total capital in an industry is evenly distributed across locations. 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. In the wage equations, the total wage bill from the employer file is the dependent variable[13].

Regarding our variables of interest, we split them in those related to "firm characteristics" and "workforce-employee characteristics". The first group includes employment, trade orientation, foreign ownership, industry, multi-location, region, collective bargaining agreement, age, turnover, R&D importance, and compensation practices. The second group includes the proportion of employees in the location by level of education, training participation, technology use, type of employment, sex, experience and occupation.

Most of the variables relating to the workforce composition used in the productivity and wage regressions are estimated from the sample of workers matched to the firm, with the exception of the occupation data which is taken from the employer file. The proportion of employees holding a university degree is calculated by dividing the number of employees surveyed that have a degree by the total number of employees surveyed in that

[11] The WES dataset also offers a subjective measure in which the employer specifies whether its productivity increased, decreased or remained unchanged in the previous year. However, since the rest of our variables are available only for 1999, this measure is of limited use for the purposes of our study.
[12] As with many other firm-level surveys, WES lacks data on capital stock. Many studies use energy costs as a proxy for capital, however this data is also not available in WES. We use industry-level data due to lack of a viable alternative, recognizing that it is an imperfect measure.
[13] We obtain very similar results by adding non-wage benefits expenses to the wage bill in our regressions (results not shown but available on request).

location. We use the same procedure to look at the interaction between human capital and technology use, calculating the proportion of employees with a given combination of learning, education and technology use. While using the employee file is preferable in that gives us a richer set of information, it also may impose large sampling errors in cases where only a few employees are interviewed in a location (particularly for large firms). However, we believe that any biases imposed by using data from the employee file are small, for two reasons. First, the importance of under-representation of employees in large firms is low in the case of WES since, as noted above, the sample is mostly composed of a large number of small locations. Moreover, Mairesse and Greenan (1999) use linked employer-employee data for the U.S. to illustrate the value of employee information even when few employees are interviewed. Even though estimates using employee information may be biased downward, their results show that consistent estimates could still be obtained as long as more than one (randomly chosen) employee is interviewed. In the instances where we have information from both employee and employer (training, technology, and occupational distribution), we empirically examine whether the results differ substantially depending on the source of the information.

There are two other data issues pointed out earlier that are worth raising again here. First, our study uses the first wave of WES for 1999, the only year available at the start of our research. This restricts our focus to determinants of productivity levels rather than growth and does not allow us to deal with the issue of unobserved firm heterogeneity. The second point is that we cannot capture the lags with which investments in human capital and technology affect productivity given that the survey questions focus on the location's activities over the most recent completed fiscal year. This problem mainly affects the ability to accurately estimate the return to training, as we can measure only the training activity that occurred in the same year as we measure productivity. Since the literature suggests that the full benefits of training occur with a lag, this suggests that our results will likely understate the employer’s return to training. The time-lag issue is less important for the technology variables, as we are focusing on technology use (which captures past and present investments) rather than implementation.

4. DESCRIPTIVE STATISTICS

Before turning to the empirical results, we provide some summary statistics about locations in our sample in Table 1A and 1B. The tables provide the mean and standard errors for key human capital, technology use and production variables, as well as data on other worker and firm characteristics. The table shows that most of the locations in our sample have less than 20 employees (84 percent), an average number of 16 employees per firm. The sample is primarily composed of domestic-owned locations, with only about 6.5 percent of locations being foreign-owned (i.e., locations with more than 50 percent of assets controlled by foreign interests).

Dummy variables were created for the highest level of education attained from the employee survey. On average, about a third of workers per location have some form of post-secondary education – 23 percent with a college diploma and just over 13 percent with a university degree.[14] Still, the largest share of workers have only a high school diploma or trade designation (32 percent), and 15 percent of employees have not completed high school. The share of workers trained among locations in our sample is similar for formal and informal training in each case about 24 percent of employees in the location received training in the past year.[15] On average, only 12 percent of employees in

[14] University-educated persons are slightly under-represented in the WES survey relative to the other surveys (i.e., university degree holders accounted for 19% of the population in 1999 according to the Labour Force Survey).

[15] Classroom training is defined as training activities with a predetermined format, pre-defined objectives, specific content and progress that can be monitored or evaluated. By definition, on-the-job training is given during work hours, at the workplace and in a location that is not necessarily separate from the production facilities. However, no formal definition of “on-the-job training” was given to respondents in the questionnaires. As discussed earlier, we focus primarily on data from the employee file to measure worker characteristics. However, interestingly there is a significant difference in the amount of informal training reported by employers and that reported by employees. This reveals one of the difficulties associated with properly measuring on-the-job training. Workers consider some learning to be part of their regular job rather than on-the-job training per se, while employers consider that learning as a part of their training expenditures. Without a formal definition of informal training in the survey, it lends itself to mismeasurement by at least one of the parties. However, our prior is that employees can better identify true training or learning more than their employers, and given our other objectives, we continue to focus on training in the employee file.

a location received computer training, yet on average 54 percent of employees in a location use computers on the job. Other popular types of training included professional training and "other".[16]

To get a sense of how important the various human capital and technology use variables are for productivity, Table 1A and 1B also present summary statistics according to whether locations are in a high-productivity or low-productivity group. The productivity groups are created by statistically sorting locations into one of the two groups according to their level of productivity.[17] This exercise reveals interesting findings from the raw data that helps guide our empirical specification. For example, in the case of education, we find that low-and-high-productivity firms do not differ substantially in their employment of persons with high school or college diplomas – the key difference is found among the most highly-educated workers. In high-productivity locations, 17.7 percent of employees have a university degree, compared to only 10.0 percent of locations in the low-productivity cluster, suggesting that the share of workers with university education is particularly important for firm productivity.

With respect to firm training, high-productivity locations train their employees more than low-productivity ones. The largest difference is for formal training; 20.0 percent of low productivity employers provided formal classroom training to employees in the year, compared to 29.5 percent of high productivity employers. Moreover, it is interesting that the type of training appears to matter as well. 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 percent of employees in low-productivity

[16] The training subject "other" was chosen by 39 percent of those who took training, reflecting a weakness in the questionnaire.

[17] The clusters are generated using the FASTCLUS procedure in SAS. This statistical procedure divides the locations into several groups so that locations in the same group are as similar as possible and locations between each of the groups are as dissimilar as possible. This method required the number of desired groups to be specified. Our objective was to divide the locations into two groups based on their value-added per employee. As a result, 1,611 firms were located in the "low-productivity" cluster while the remaining 2,230 firms were considered "high productivity".

locations received training on computers, compared to 18.5 percent in the high-productivity cluster.

Technology use can include using a computer, computer-assisted/controlled technologies, or other machine or technological devices. As mentioned above, the majority of employees at locations in our sample use a computer. As expected, we see that computer use is much more prevalent among employees in the high-productivity location cluster – 66 percent versus 47 percent in low-productivity clusters. However, the same is not true for other types of technology use. There is no statistical difference between the share of workers using computer-controlled technologies in low and high-productivity clusters. The share of workers using "other types of technology" (including devices such as fax machines) is more common among employees in low-productivity firms. Thus at least in the raw data, there appears to be something special about computer use for labour productivity.

WES also collects data on how workers use computers at work. There are thirteen application types and respondents specify as many applications as applicable. To capture the pervasiveness of technology use within the location, we group the application types into two broad categories: general and advanced use. General use includes applications that apply to a number of different job types, such as word processing, spreadsheets, database management, communications, general management applications, graphics and presentations. Advanced or specific use is defined as computer programming, data analysis, computer-aided design and engineering, expert systems, and desktop publishing. Table 1A shows that high-productivity locations are more likely to have employees using computers for both advanced and general uses, but that the gap between low-and-high-productivity locations is larger for general uses. Similarly, the share of non-management workers using a computer is also much larger in the high productivity cluster. Both of the above observations from the raw data suggest that the more widely used a technology is within the firm, the higher the productivity payoff.

Under the hypothesis that investments in education, training and technology use are closely linked, we look at participation in training and computer use by level of educational attainment in Table 2. The data show that those without a minimum of a high school diploma are less likely to engage in learning activities or use a computer in their daily work. The share of employees participating in formal training and using a computer increases considerably with each education level. While the share of workers participating in on-the-job training and computer training tend to rise with education as well (at least up to the bachelor level), the gap between education levels is much smaller than for the other variables. For example, among those with education above the high-school level, essentially one-third of employees learn through on-the-job training across higher-education levels (again, with the exception of advanced-degree holders which tend not to report as much of this type of training). The finding that informal classroom training is less closely linked to education was also observed by Livingstone (2001) using the *New Approaches to Lifelong Learning Survey*. As well, there is little difference between the participation rates of college graduates and university graduates in terms of computer training; however, there is still a sizeable gap between educated and less-educated workers. The range between the low and high skilled is most striking in the case of computer use, where 88 per cent of university degree holders (or 90 percent of advanced-degree holders) use a computer compared to only 25 per cent of those with less than a high school diploma.

The summary statistics for the interaction terms at the location level are provided in Table 1A. Among the 54 per cent of workers in our sample using a computer, 35 per cent did not have a university degree and had not received computer training in the year. The share of computer users who did not have a university degree but had been trained on computers was approximately equal to those who had a university degree and did not receive training, at about 8 per cent of employees in our firms. Only a small proportion of employees in a location satisfied all three criteria (3 percent). However, we see that the share of workers with these characteristics is over more than five times higher in high-productivity locations than in low-productivity ones on average. The regression analysis will allow us to determine whether the combination of these characteristics makes a large difference to productivity, as well as information on the extent to which training compensates for education.

Turning finally to our control variables, a few points of interest arise. High-productivity firms 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 percent of high-productivity firms, compared to only 6 percent 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. Thus, profit-sharing is the only compensation scheme we include among the firm control variables in the empirical analysis.

One of the interesting features of the WES is that we can classify locations by ownership as well as export orientation. One of the standard findings in micro-level productivity studies for Canada has been that foreign-owned firms are more productive than domestic-controlled firms (e.g., Baldwin and Dhaliwal, 2001). However, recent research for Canada has suggested that trade orientation actually matters more for both productivity and innovation than ownership per se (Baldwin and Gu, 2002; Baldwin and Hanel, 2000). That is, while foreign firms are more productive than domestic firms, they are not necessarily superior to domestic multinationals -- firms that share an outward focus or global orientation. In our sample, outward-oriented locations are defined as those who sell the largest share of their sales to the international marketplace. Our data show that not only is foreign ownership more common in the high-productivity cluster, but domestic firms with an outward orientation are more prevalent in the high-productivity cluster as well (although they still comprise a very small share of the sample). 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.

This section has pointed out some key relationships that emerge from looking at locations by their level of productivity. In order to sort out the most important determinants of productivity and wages, controlling for a wide variety of firm and worker characteristics, we now turn to the econometric analysis.

5. ECONOMETRIC RESULTS

5.1 All locations and workers

Table 3 presents the results from estimating both the productivity and earnings equations for our sample of locations and the workers they employ. First, we estimate equations (3) and (5) including only the production variables and our main variables of interest – the human capital and technology use variables. Columns (1) and (3) of Table 3 report the estimated coefficients. As expected, the share of workers with a university degree, receiving training and using computers on the job are all significant determinants of productivity and wages. Computer use is found to make the largest single contribution, with a 10 percentage point increase in the share of workers using computers raising productivity by 5.0% and raising wages by 3.5%. The share of workers receiving on-the-job training is not found to significantly affect productivity, while an increase in the share of workers receiving formal or classroom training in the year is associated with 3.5% higher productivity with a similar wage benefit to workers. By type of training, computer training is the only type which has a significant and positive effect on firm productivity, with an estimated coefficient close to that of computer use. The unconditional returns to education and formal training in the production equation are similar to those in the wage equation; however, computer use and training on computers provide much larger benefit to firms in terms of higher productivity than to workers in terms of higher wages.

The findings on the type of technology used is consistent with our observations from the raw data. Specifically, firms using a larger share of "other types" of technology are found to have lower productivity and wages. Using a computer for advanced or specific uses provides no additional productivity benefit or wage gain.

To determine whether the estimated coefficients in the unconditional regression are partly picking up productivity variations associated with firm, worker, industry or regional characteristics, we introduce control variables in columns (2) and (4) of Table 3.[18] Among the variables of interest, the computer use and training variables are most affected by the inclusion of control variables.

Technology use

The estimated impact of a 10 percentage point increase in computer use on productivity falls from 5.0% in the unconditional regression to 2.9% in the regression with controls. The slight drop in the estimated coefficient likely reflects the fact that the relatively more productive industries in our sample include high ICT-use industries, such as wholesale trade, finance, insurance and real estate, business and information services. Among the four most ICT-intensive use industries in our sample, ICT investment has increased by a combined 57 percent over the period 1996-99 according to national data.[19] Thus, the higher coefficient in the unconditional regression was likely picking up some of these industry effects. The negative impact of "other technology" use on productivity and wages in the unconditional regression also becomes insignificant when we control for firm and industry characteristics, reflecting the fact that intense users for low-technology devices tend to have lower productivity for other reasons.

Overall, the industries that have the highest productivity levels relative to the omitted retail sector in our sample include mining, wholesale trade, transportation equipment production, and science-related industries (pharmaceuticals, medicine manufacturing and aerospace). Recognizing that we are capturing differences in productivity levels as opposed to productivity growth, it should not be surprising that ICT-producing goods and services industries do not emerge as the most productive sectors. ICT-producing industries experienced a strong pick-up in productivity growth late in the 1990s, but as of 1998-99 national data confirm that their productivity level was below industries such as

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[18] The addition of industry dummies will clearly remove the explanatory power of the capital-labour ratio, as within-industry variation mainly comes from differences in employment (by definition capital is distributed equally across firms within each detailed industry). Omitted industry categories include the retail trade sector, Ontario, inward-oriented domestic-owned locations, and the proportion of production workers.

[19] Based on unpublished data from Statistics Canada.

wholesale trade, for example. Moreover, other research has shown that ICT use has a greater impact on productivity than ICT production.

Our results on computer use suggest that the more intensely technology is used within the firm (i.e., the higher the share of workers using a computer), the higher is productivity. Another indication of the extent of technological diffusion throughout the organization, as noted by Black and Lynch (2000), is the share of non-executive employees who use a computer. Although not reported here, we also separate computer use into managerial and non-managerial use and find that the share of non-managers using a computer has a positive and significant impact on productivity, even stronger than managerial technology use.

Human capital

Education remains a significant determinant of the level of productivity in the conditional regression, with a 10 percentage point increase in the share of workers with a university degree generating 2.1% higher productivity. However, with the inclusion of control variables for worker characteristics, the wage return to workers of a university degree is now only half as large as the productivity return to the firm. In the next section we jointly estimate the wage and productivity equations and test whether differences in pair-wise coefficients are significant.

In the conditional regressions, both on-the-job and formal training become insignificant at the 10 percent level in both the productivity and wage equations. While previous research has generally found a large and significant productivity return to structured training, it is worth re-iterating here 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 training variables is perhaps not surprising. That said, consistent with the findings of Black and Lynch (1996), the coefficient on computer skills training remains a highly significant determinant of firm productivity. The results show that a 10 percentage point increase in the share of workers using computers is associated with 4.5% higher productivity. This suggests that it is not so much the quantity of training provided, but the subject matter of that training that matters for productivity.[20] Moreover, although not shown here, 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 behind the productivity gains. 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 (i.e., team-building or professional training), 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 return to firms is much larger than the return to workers in the case of computer training, consistent with the empirical literature (i.e., Dearden et al., 2000).

Other determinants of productivity

We observe some interesting results relating to the effect of the control variables themselves on productivity. In terms of ownership, we find support for results found in other Canadian studies using different data. For example, as in Baldwin and Gu (2002), our results suggest that trade orientation is more important for firm productivity than ownership per se. While productivity is not significantly higher among the foreign-owned locations in our results, the productivity of a location that is domestic but outward-oriented was 40% higher than that its inward-focused counterpart.[21] 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 more wages.

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[20] Arguably, the 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) in Section 5.5, we find no substantial difference in the results.

[21] The estimated coefficient on outward-orientation is 0.276. The percentage impact on productivity in moving from 0 to 1 in the outward-oriented dummy variable in our semi-log regression is approximated by $(e^b - 1)*100$. For the remainder of the discussion we will refer to the percentage change calculated by this formula for the dummy variables at the firm level. This is in contrast to the worker characteristics controls which are calculated as shares, such that the estimated coefficient represents the percentage change in productivity for a 1 percentage point increase in the share of workers with the particular characteristic.

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 significant once we control for other factors. Similarly, Baldwin and Sabourin (2001) 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.

We find that the use of a profit-sharing compensation scheme is associated with 23% higher productivity and 14% higher wages. In contrast with Black and Lynch (2000), we find that higher employee turnover significantly diminish productivity and wages. Moreover, the share of employees working non-standard hours (i.e., temporary or part-time workers) has a negative and significant effect on both productivity and wages. Our results suggest that the share of workers covered by a collective bargaining agreement leads to a higher wage bill but the effect on productivity is insignificant (although it was not statistically different than the wage premium).

5.2 The return to the firm versus the return to the worker

In order to test whether the observed differences between productivity and wage returns are significant, we calculate Wald tests on the equality of the estimated coefficients.[22] Based on the test statistics, we cannot reject the null hypothesis that all the pair-wise coefficients from the two regressions are statistically equal, with the notable exception of computer training.

When it comes to computer training, the benefits to the firm far exceed those to the worker and this difference is statistically significant. That is, the 4.5% increase in productivity associated with a 10 percentage point increase in the share of workers receiving computer training is statistically higher than the share passed on to workers (1.2%, albeit insignificant at the 10% level). However, for all other groups of workers, the results suggest that productivity gains are reflected in worker wages, as also found in

[22] The results are not presented in Table 3 but are available from the authors upon request.

Jones (2001) in the case of education. This provides general support for the standard microeconomic theory assumption that workers are paid according to their marginal products.

It is important to raise a cautionary note about the interpretation of the results for some groups of workers. There are certain important control variables that have not been included in our regressions. An important example is in the case of females. We are not able to control for hours worked, which may be largely responsible for the negative relationship between the share of female employees and productivity and wages.

5.3 By sector and type of firm

As noted earlier in the paper, previous research on technology use in Canada has focused primarily on the manufacturing sector. A major contribution of this paper is the ability to include the services sector (in the non-manufacturing sector[23]) which comprises a larger share of the economy and is a major user of new technology. We also examine whether the impact of human capital and technology use on productivity varies by size of firm. Thus, we split our sample into four sub-samples: manufacturing versus non-manufacturing industries, and small versus large firms. We then estimate equations (3) and (5) for each sub-sample.

Manufacturing versus non-manufacturing

Table 3A provides regression results from the productivity and wages equations run on the manufacturing and non-manufacturing sub-samples, showing only the variables of most interest – education, training and technology use.[24]

The results show that the non-manufacturing sector is driving the results in the full sample regarding computer training and education. While the return to computer use to the firm and the worker is similar in both sectors of the economy, human capital plays a

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[23] The non-manufacturing sector includes all service-producing industries (wholesale and retail trade, transportation and storage, ICT and business services, health and social services, information and cultural services), agriculture, mining, construction and utilities. See Appendix A for the industry codes (NAICS).
[24] All regressions in Tables 3A – 3C include the production and control variables, as in Table 3.

very different role. Consistent with the findings of Black and Lynch (1996), we find that training on computers raises the productivity only of non-manufacturing firms; the estimated coefficient on computer training in the manufacturing sector is negative and insignificant. Specifically, a 10 percentage point increase in the share of workers receiving computer training raises productivity by 5.4% in the non-manufacturing sector.

Black and Lynch (1996) find that instead formal training outside working hours raises productivity in the manufacturing sector. While we also find that formal training has a positive effect on productivity in the manufacturing sector, the estimated coefficient is insignificant.[25] Nevertheless, we do find a positive and significant effect of formal training on the wage bill in the manufacturing sector, while the same is not found for the non-manufacturing sector.

With respect to education, both manufacturing and non-manufacturing firms who employ more educated workers have appreciably higher productivity. The coefficient on education implies that for a 10 percent increase in education, productivity would rise by 4% in manufacturing and 2.6% in non-manufacturing. These estimates are similar to those estimated in previous studies for the manufacturing sector, although our estimates for the non-manufacturing are somewhat lower. Nevertheless, we find that only in the non-manufacturing sector is the productivity gain also reflected in higher wages for workers.

Among the control variables not reported in the table, it is noteworthy that the higher productivity realized by outward-oriented firms is evident in both the manufacturing and non-manufacturing industries. Specifically, in an outward-oriented domestic location is 26% higher than its domestic counterpart in the manufacturing sector and 30% higher in the non-manufacturing sector.

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[25] This may reflect definitional differences as cannot distinguish between formal training outside working hours from that within. Thus, in the case of Black and Lynch (1996), the measuring training outside working hours implies no loss of production whereas it would include time away from work in our case.

Small versus large firms

In Table 3B we split our sample into small and large firms. Small firms are defined as those with less than 20 employees and large firms capture the remainder. Establishments with less than 20 employees account for approximately 30% of employment in Canada.[26]

We find that education matters most for productivity in small locations. A 10 percentage point increase in the share of university educated workers raises productivity by 2.3% among small locations, compared to an increase of 1% for large firms (although the latter is insignificant at the 10% level). We find that formal training is associated with higher productivity in large firms, consistent with the findings for the manufacturing sector as manufacturers tend to be larger firms.

Splitting the sample by size reveals that the large differential observed in the full sample between the productivity and wage gain regarding computer training is also driven by small locations. Locations with less than 20 employees have the most to gain from computer training in terms of productivity (4.9% gain for a 10 percent point increase in the share of workers receiving training), yet only workers in larger firms tend to see the benefit reflected in higher wages.

Not surprisingly, the productivity benefit associated with selling the firm's products and services primarily to an international market is driven by locations with greater than 20 employees. The coefficient on outward-orientation is insignificant for small locations with less than 20 employees.

5.4 Employee versus employer data

As noted in section 3, one of the criticisms of using data from the employee and linking it to the employer is that sampling errors are imposed in cases where only a few employees are interviewed in a location. We use employee data for all worker control variables that are not available at the firm level, as well as for variables that we think the employee can provide more accurate information (training and computer use). In the latter case, we can test whether our results are affected by this choice. Although not reported here, we re-estimate our model using training and computer use data from the employer data file to see whether our results are sensitive to the source of information. We find that they are not. As in the previous regressions using employee information, general on-the-job and formal training are not found to have a significant impact on productivity (information on type of training is not available at the employer level). The estimated effect of a 10 percentage point increase in the share of workers using a computer increases productivity by 2.9% using employer data, versus 3.2% using employee data. This supports our view that any biases from using averages of employee data at the employer level are small.

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

To this point we have shown that computer use, computer training and university education are associated with higher productivity, particularly in the non-manufacturing sector and in small locations. As described in Section 4, to explicitly examine the relationship between technology use and human capital on productivity and wages, we create a set of interaction terms between workers who use a computer and their human capital characteristics. That is, we create variables for all combinations of computer users with and without a university degree and with and without computer training. This allows us to infer something about the way in which these three factors work together in their contribution to productivity at the location level. We re-estimate equations (3) and (5) using these worker interaction terms, in addition to the individual control variables for education and training, and the same production and control variables used in the previous regressions.

The results are presented in columns (2) and (4) of Table 4. 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

[26] Statistics Canada's Labour Force Survey, 1999

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 raises firm productivity by 6 per cent, in addition to the gain from an increase in the share of university workers alone.

Interestingly, we also find a large productivity gain from an increase in the share of workers who do not have a university degree but participate in computer training and use a computer. An increase in the share of this type of worker also yields 7 per cent higher productivity. This suggests that computer skills training can adjust 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 suggested that the productivity-enhancing aspect of computer training reflected on-the-job training. Thus in Table 4A, 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 but participating in classroom training is not found to 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 don't have a university degree but receive computer training, the productivity gain comes both from classroom and on-the-job training. As we might expect, this suggests that less-skilled workers 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.

6. CONCLUSIONS AND FUTURE RESEARCH

This paper examines the effect 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.

We find that for a 10 percentage point increase in the share of workers receiving computer training, productivity rises by 4.5% and a 10 percentage point increase in the share of workers using a computer and with a university degree raises productivity by 2.9% and 2.1%, respectively.

A number of our findings have interesting policy implications relating to productivity. We find evidence that computer skills training can adjust 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.

An important contribution of our research for Canada is the inclusion of the non-manufacturing sector. We find that the relationship between human capital, technology use and productivity is not the same in all firms and industries. While education and technology use are important determinants of productivity in both sectors of the economy (manufacturing and non-manufacturing), the impact of training differs. Our finding that an increase in the 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 a positive and significant effect on location-level productivity in this sector. The effect of human capital and technology use also differs by firm size. Employing a higher share of workers with a university degree and using a computer is found to be more important in locations with less than 20 employees than in larger locations. Larger locations, in contrast, realize a larger productivity benefit from a higher share of workers receiving formal training.

Finally, our study supports previous research for Canada which shows 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. Outward-oriented firms are found to have 32% higher productivity than their inward-focused counterparts, even after controlling for a range of other factors. The relationship between outward orientation and productivity holds in both the manufacturing and non-manufacturing sectors.

When we simultaneously estimate the production and wage equations, we find that in cases where there is a higher share of workers engaging in on-the-job computer training, the productivity benefit to the firm exceeds the wage gain to workers. In all other cases, the pair-wise coefficients in the productivity and wage equations are not statistically different, supporting the theoretical assertion that worker wages reflect their marginal productivities.

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. Future research will be necessary to draw stronger conclusions than just those factors that are associated with higher productivity. Since we have used the first wave of WES only, we cannot address the issue of causality. Several studies have shown that results based on cross-sectional data are not supported in fixed effects models which control for unobserved heterogeneity (e.g., McGuckin et al., 1998). It may be true that good performers are just more likely to use advanced technologies, employ educated workers and train their employees than poorly performing plants. Thus, we cannot draw conclusions from our research on the factors that *cause* productivity growth at the firm level.

However, 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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Appendix A : Definition of variables used

I) Main Variables

Number of employees in the location: Number of people employed at this location in the last pay period of March 1999.

Expenses on material (proxy): Gross operating expenditures minus total gross payroll and expenses on non-wage benefits and on training.

Value added: Gross operating revenue minus expenses on material.

Labour Productivity: Value added divided by number of employees in the location.

Payroll by worker: Total gross payroll for all employees at this location between April 1, 1998 and March 31, 1999 divided by the number of employees in the location.

Capital Stock (proxy): Average stock of capital over the period 1994-98 divided by the number of employees in the location. The average stock of capital over the period 1994-98 is approximated by taking the stock of capital of the industry where the workplace evolved (at the four digits for the manufacturing sector and three-digits otherwise) divided by the number of workplace in that particular industry. Data for the average stock of fixed non-residential capital is from the CANSIM database (geometric infinite end-year depreciation, constant 1992 dollars). The number of workplace by industry is calculated by adding WES weight for each location by industry.

II) Workforce Composition (W)

Percentage of workers trained (proxy): Number of workers trained divided by the number of employees surveyed in the location. Training should have been received in the past 12 months and been provided or paid by the employer. We distinguished between two types on training: classroom[27] training and on-the-job training. In addition, we have grouped them in four main subjects “computer hardware or software”, “professional, managerial, sales and marketing”, “team-building and group-solving” and “other (orientation, health, safety, etc.)”.

Percentage of workers by level of education (proxy): Number of workers with a given diploma divided by the number of employee surveyed in the location. We distinguish among the following types of diplomas: less than high school, high

[27] Classroom training includes all training activities which have a pre-determined format, a specific content and for which progress may be evaluated.

school diploma only, college and some university, bachelor's completed and higher than a bachelor's degree.

Percentage of workers using different types of technologies (proxy): Number of workers using different types of technologies divided by the number of employee surveyed in the location. We can distinguish among three main types of technologies: Computer, computer-controlled or computer-assisted technologies (industrial robots, retail scanning system, CAD/CAM system, etc.) and other machine or technological device (cash registers, sales terminal, scanners, manual typewriters, industrial machinery and vehicles).

Percentage of non-standard workers (proxy): Number of workers non permanent and /or at part-time divided by the number of employee surveyed in the location.

Percentage of female workers (proxy): Number of female workers divided by the number of employee surveyed in the location. Training should be received in the past 12 months and be provided or paid by the employer.

Average years of experience (proxy): Average years of experience on the labour market of employees surveyed in the location.

Percentage of workers by occupation: Number of workers in a given occupation (part-time and full-time) divided by the number of employees in the location. We distinguish among seven types of occupation: manager, professional, technical, sales or marketing, administrative, unskilled workers and others.

III) Firms' characteristics (X)

Most important market for sales: Market with the highest market sales in percentage of total sales among "local", "rest of Canada", "USA or rest of the World". Outward oriented firms are those for which the most important market for sales is "USA or the rest of World".

Foreign-owned locations: Locations where more than 50 percent of the assets of this workplace are held by foreign interest assets.

Multi-location workplace: Workplace owned by a greater entity made by more than one location.

Location covered by a collective bargaining agreement: Workplace for which one or more than one employee are covered by a collective bargaining agreement.

Age of the location (proxy): Number of years the workplace has been located at the actual address.

Turnover: Sum of number of new employees hired and employees permanently left between April 1, 1998 and March 31, 1999 divided by the average number of employees in the location in the last two pay periods of March 1999 and March 1998.

Innovation: Introduction of new goods/services, improved goods/services, new processes or improved processes between April 1, 1998 and March 31, 1999.

Technology use: Introduction of a major new software application and/or hardware installation, computer-controlled or computer-assisted technology, or any major technologies or machinery between April 1, 1998 and March 31, 1999.

Compensation practices: The compensation system in the location can includes four types of compensation: individual incentive systems, productivity or quality gain-sharing, profit-sharing plan, merit-pay or skill-based pay.

R&D focus: The relative importance of "undertaking research and development" or "developing new products or new production/operating techniques" strategies are important, very important or crucial.

Industrial Sector: Industrial sectors are "Manufacturing labour-intensive (NAICS: 311-312-313-314-315-316-337-339)", "Manufacturing primary products (NAICS: 321-322-324-327-331)", "Manufacturing secondary products (NAICS: 325-326-332 excluding 325410)", "Manufacturing transportation equipment (NAICS: 336 excluding 336410)", "Manufacturing machinery and electrical (NAICS: 323-333-335 excluding 335920)", "Manufacturing ICT (NAICS: 334110-334210-334220-334290-334410-334511-334512-335920)", "Manufacturing other science-based (NAICS: 336410-325410-334310-334610)", "Forestry and primary activities (NAICS: 113-114-115)", "Mining (NAICS: 21)", "Construction (NAICS: 23)", "Utilities (NAICS: 22)", "Wholesale trade (NAICS: 41)", "Retail trade and personal services (NAICS: 44-45, 713-721-722-811-812)", "Transportation and storage (NAICS: 48-49)", "FIRE" (NAICS: 52-53), "ICT and business services (NAICS: 5133-514191-54-55-56)", "Health and social services (NAICS: 621-622-623-624-813)", "information and cultural services (NAICS: 511-512-5131-5132-514-711-712 excluding 514191)".

Region: Industrial sectors are "Atlantic provinces", "Québec", "Ontario", "Alberta, Saskatchewan and Manitoba", "British Columbia".

Appendix B: Tables

Table 1A
Descriptive Statistics

	Statistics		Productivity clusters		
	Mean	Standard deviation	Low	High	t-test
Dependant variables					
Log value added/employee	10.543	0.036	9.948	11.368	***
Log payroll/employee	9.951	0.026	9.673	10.361	***
Value added/employee ($1,000)	53,567	2379	23,950	107,130	***
Revenue/employee ($1,000)	124,081	4197	74,178	202,174	***
Material/employee ($1,000)	70,423	2940	50,228	95,043	***
Pay/employee ($1,000)	25,310	570	18,164	35,654	***
Production variables					
Log (capital/location)	12.487	0.048	12.403	12.614	**
Capital/location ($1,000 000)	1,450	114	1,016	2,083	***
Log(number of workers)	1.998	0.030	1.985	2.018	
Number of workers per location	15.626	0.522	13.933	18.392	***
Less than 20 employees	0.841	-	0.848	0.824	
Between 20 and 49 employees	0.110	-	0.110	0.115	
Between 20 and 99 employees	0.031	-	0.030	0.036	
More than 100 employees	0.018	-	0.013	0.025	***
Education, training, techology use *(% of employees)*					
Less than high school diploma	0.147	0.010	0.168	0.113	***
High school diploma, trade vocational course or industry certified	0.319	0.012	0.332	0.309	
Some college degree or university	0.177	0.010	0.183	0.172	
Completed college and university below bachelor's degree	0.228	0.011	0.220	0.239	
University degree completed	0.134	0.011	0.100	0.177	***
Bachelor's degree	0.096	0.009	0.073	0.120	***
Advanced degree	0.038	0.005	0.027	0.056	***
Share of workers trained in "classroom"	0.236	0.012	0.200	0.295	***
Share of workers trained "on-the-job"	0.241	0.011	0.234	0.265	
Share of workers who took a training on sotware/hardware	0.121	0.009	0.085	0.185	***
Share of workers who took classroom training on sotware/hardware	0.053	0.005	0.036	0.080	***
Share of workers who took on-the-job training on sotware/hardware	0.077	0.008	0.053	0.119	***
Share of workers who took a professional training	0.138	0.011	0.142	0.138	
Share of workers who took a training on team-building	0.012	0.002	0.013	0.011	
Share of workers who took any other types of training	0.168	0.014	0.170	0.171	
Share of workers using a computer	0.539	0.018	0.469	0.662	***
Share of managers using a computer	0.119	0.008	0.106	0.137	*
Share of non-management workers using a computer	0.420	0.016	0.363	0.525	***
Share of workers using computer-controlled technologies	0.119	0.010	0.112	0.126	
Share of workers using any other types of technologies	0.331	0.014	0.373	0.267	***
Share of workers using a computer for advanced use	0.270	0.012	0.233	0.330	***
Share of workers using a computer for general use	0.427	0.015	0.359	0.543	***
Share of workers not using a PC	0.461	0.018	0.531	0.338	***
Share of workers using a PC, without univ. and without training on PC	0.346	0.014	0.328	0.393	**
Share of workers using a PC, without univ. and with training on PC	0.083	0.006	0.064	0.119	***
Share of workers using a PC, without univ. and trained in classroom on PC	0.038	0.004	0.028	0.055	***
Share of workers using a PC, without univ. and trained on-the-job on PC	0.052	0.005	0.040	0.073	***
Share of workers using a PC, with univ. and without training on PC	0.080	0.008	0.067	0.090	*
Share of workers using a PC, with univ. and with training on PC	0.030	0.006	0.011	0.060	***
Share of workers using a PC, with univ. and trained in classroom on PC	0.011	0.002	0.004	0.023	***
Share of workers using a PC, with univ. and trained on-the-job on PC	0.021	0.006	0.008	0.042	**

*There are 4219 locations and 24697 employees in our sample. The sample is resticted to locations where at least two employees were surveyed.

Table 1B
Descriptive Statistics

	Statistics		Productivity clusters		
	Mean	Standard deviation	Low	High	t-test
Workforce Characteristics					
Share of non-standard employees	0.367	0.014	0.395	0.306	***
Share of females in workforce	0.549	0.015	0.595	0.478	***
Average experience	15.665	0.301	15.076	16.567	**
Average experience squared/100	2.989	0.092	2.822	3.268	**
Share of professional	0.079	0.009	0.066	0.096	*
Share of management	0.163	0.007	0.159	0.175	
Share of technical workers	0.148	0.012	0.132	0.175	*
Share of sales workers	0.179	0.010	0.147	0.232	
Share of administrative workers	0.141	0.014	0.147	0.118	***
Share of unskilled workers	0.217	0.013	0.264	0.157	***
Share of other workers	0.074	0.010	0.086	0.046	**
Firm Characteristics					
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	**
Multi-plant location	0.191	-	0.180	0.208	
Share of workers covered by CBA	0.085	0.009	0.067	0.116	**
Years in same location	12.594	0.478	11.889	13.418	
Employee turnover	0.534	0.027	0.621	0.414	***
Profit-sharing compensation	0.091	-	0.056	0.145	***
Merit-based compensation	0.203	-	0.202	0.225	
Incentive-based compensation	0.355	-	0.329	0.402	*
Gains-sharing compensation	0.092	-	0.089	0.098	
R&D is a high priority	0.234	-	0.202	0.286	***
Introduction of a new product/service	0.368	-	0.365	0.366	
Imroved product/service	0.400	-	0.381	0.425	
Introduction of a new process	0.258	-	0.233	0.283	
Improved process	0.315	-	0.287	0.339	
Implementation of a new software/hardware	0.245	-	0.187	0.322	***
Introduction of a new computer-controlled technology	0.052	-	0.042	0.071	*
Introduction of any other major technologies	0.054	-	0.057	0.037	
Industry					
Labour-intensive manufacturing	0.031	-	0.037	0.025	*
Primary manufacturing	0.013	-	0.012	0.015	
Secondary manufacturing	0.019	-	0.014	0.024	**
Transportation equipment	0.004	-	0.002	0.007	**
Machinery & electrics	0.020	-	0.014	0.030	***
ICT-based industries	0.004	-	0.004	0.004	
Other science-based industries	0.002	-	0.002	0.003	
Forestry	0.010	-	0.009	0.012	
Mining	0.009	-	0.004	0.015	***
Construction	0.073	-	0.067	0.090	
Utilities	0.003	-	0.002	0.003	
Wholesale	0.093	-	0.050	0.157	***
Retail	0.381	-	0.486	0.199	***
Transportation & storage	0.048	-	0.051	0.039	
FIRE	0.077	-	0.058	0.104	***
ICT services and business services	0.119	-	0.103	0.148	*
Health & social services	0.082	-	0.071	0.109	**
Information & culture	0.013	-	0.013	0.015	
Region					
Atlantic	0.087	-	0.085	0.091	
Quebec	0.211	-	0.237	0.179	*
Prairies	0.190	-	0.208	0.165	*
BC	0.146	-	0.130	0.180	**
Ontario	0.365	-	0.340	0.385	

Table 2
Employee Training and Computer Use by Education Level

	% of employees					
	Participated in:					
Highest level of education attained	Formal classroom training	On-the-job training	Computer training	Classroom computer training	On-the-job computer training	Technology use
Less than high school diploma	22.6	20.5	6.3	2.3	3.7	24.7
High school graduate*	35.3	27.6	16.1	9.7	8.1	51.6
Some post-secondary	40.7	31.9	21.6	14.1	10.4	68.2
Non-univ. post-secondary diploma	43.7	33.6	26.0	16.2	12.7	74.5
University degree	50.6	32.3	28.5	18.9	12.3	87.9
Bachelor's degree	50.1	34.0	28.8	18.8	12.8	87.0
Advanced degree	51.8	28.1	27.6	19.0	10.9	90.0

Note: High school graduation also includes those with a trade or vocational certificate. Some post-secondary education includes those who took some college or university but did not graduate. College diploma or certificate includes those who received a college diploma or university certificate (below the bachelor's level). Bachelor's degree includes those with teacher's college. Advanced degrees include all university education above the bachelor's level.

Table 3
Location-level value added and earnings functions: Basic models

	(A) Value added function		(B) Earnings function	
	Without controls	With controls	Without controls	With controls
	(1)	(2)	(3)	(4)
Production variables				
Log (capital/workers)	0.066 ***	0.008	0.054 ***	-0.017
Log (employment)	-0.035	-0.057 *	0.021 *	0.014
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
With professional training	-0.317	-0.291	-0.155	-0.080
With team-building training	-0.194	-0.221	0.271	0.169
Technology use				
Share of workers using computers	0.502 ***	0.286 **	0.353 ***	0.187 ***
Share using computers for advanced uses	-0.192	-0.178	0.005	-0.012
Share of workers using computers-controlled techn.	-0.214	-0.042	-0.131	-0.039
Share of workers using other types of techn.	-0.081 *	-0.041	-0.138 *	-0.006
Workforce Characteristics				
Share of non-standard employees**	...	-0.219 **	...	-0.126 **
Share of females in workforce	...	-0.244 ***	...	-0.183 ***
Experience	...	-0.002	...	0.017 **
Experience-squared/100	...	-0.006	...	-0.029
% of professionals	...	0.176	...	0.444 ***
% of management	...	0.257	...	0.311 ***
% of technical workers	...	0.254 **	...	0.317 ***
% of administrative workers	...	0.334 **	...	0.335 ***
% of sales workers	...	-0.023	...	0.075
Firm Characteristics				
Outward-oriented domestic	...	0.333 ***	...	0.207 ***
Foreign-owned firms	...	0.106	...	0.028
Multi-plant location	...	0.100	...	0.062
Share of workers covered by CBA	...	0.142	...	0.198 ***
Years in same location	...	0.003	...	0.001
Employee turnover	...	-0.076 *	...	-0.043 *
Profit-sharing compensation	...	0.209 **	...	0.128 ***
R&D is a high priority	...	0.046	...	0.047 *
Industry				
Labour-intensive manufacturing	...	0.156	...	0.291 ***
Primary manufacturing	...	0.355 ***	...	0.471 ***
Secondary manufacturing	...	0.439 ***	...	0.565 ***
Transportation equipment manuf.	...	0.673 ***	...	0.517 **
Machinery & electrics manuf.	...	0.472 ***	...	0.535 ***
ICT manufacturing	...	-0.086	...	0.442 ***
Other science-based industries manuf.	...	0.710 ***	...	0.616 ***
Forestry	...	0.270 **	...	0.499 ***
Mining	...	0.768 ***	...	0.715 ***
Construction	...	0.384 ***	...	0.552 ***
Utilities	...	0.079	...	0.261 ***
Wholesale	...	0.720 ***	...	0.488 ***
Transportation & storage	...	0.223 *	...	0.460 ***
FIRE	...	0.436 ***	...	0.364 ***
ICT and business services	...	0.100	...	0.215 **
Health & social services	...	0.389 ***	...	0.195 **
Information & culture	...	0.226 *	...	0.308 **
Region				
Atlantic	...	-0.001	...	-0.055
Quebec	...	-0.059	...	-0.095 **
Prairies	...	-0.037	...	0.009
BC	...	0.074	...	0.037
Intercept	9.440 ***	10.144 ***	8.853 ***	9.351 ***
Sample Size	4,219	3,863	4,447	4,070
R-squared	0.139	0.287	0.200	0.498

Equations are jointly estimated using nonlinear least squares. Dependent variables: (A) log value added per worker; (B) log wage bill per worker. R-squared based on individual regressions.
These results are available upon request.
Significance (p-value under a t-test): ***1% level; **5% level; *10% level.

Table 3A

Location-level value added and earnings functions: Basic models

	Manufacturing		Non-manufacturing	
	(A) Value added function	(B) Earnings function	(A) Value added function	(B) Earnings function
	With controls	With controls	With controls	With controls
	(2)	(4)	(2)	(4)
Education				
% with University degree	0.402 *	-0.279 *	0.262 *	0.175 **
Training				
Share of workers trained on-the-job	0.157	0.038	-0.122	-0.090
Share of workers trained in class	0.201	0.319 ***	0.046	0.030
With computer training	-0.334	-0.268 **	0.539 **	0.165 *
With professional training	-0.312	-0.103	-0.243	-0.089
With team-building training	-0.966 *	-0.807 **	-0.307	0.185
Technology use				
Share of workers using computers	0.255 *	0.161 *	0.312 ***	0.207 ***
Share using computers for advanced uses	-0.031	0.030	-0.189	-0.015
Share of workers using computers-controlled techn.	-0.075	-0.012	-0.029	0.043
Share of workers using other types of techn.	-0.003	-0.051	-0.035	-0.005
N	1,028	1,067	2,835	3,003
R-squared	0.240	0.338	0.300	0.510

Equations are estimated 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, as per Models [2] and [4] of Table 3

Significance (p-value under a t-test): ***1% level; **5% level; *10% level.

Table 3B

Location-level value added and earnings functions: Basic models

	Small locations (less than 20 emp.)		Larger locations (20 emp. and more)	
	(A) Value added function	(B) Earnings function	(A) Value added function	(B) Earnings function
	With controls	With controls	With controls	With controls
	(2)	(4)	(2)	(4)
Education				
% with University degree	0.229 *	0.153 **	0.101	-0.269 *
Training				
Share of workers trained on-the-job	-0.090	-0.057	-0.233	-0.057
Share of workers trained in class	-0.002	0.079	0.478 **	-0.010
With computer training	0.485 ***	0.093	0.315	0.326 *
With professional training	-0.330 *	-0.153 *	0.393	0.187
With team-building training	-0.348	0.150	0.167	0.170
Technology use				
Share of workers using computers	0.335 ***	0.197 ***	0.254	0.417 ***
Share using computers for advanced uses	-0.219	0.002	-0.107	-0.346 **
Share of workers using computers-controlled techn.	0.094	0.077	-0.584 *	-0.278 **
Share of workers using other types of techn.	-0.049	-0.006	-0.063	0.002
N	1,589	1,696	2,274	2,374
R-squared	0.305	0.500	0.409	0.601

Equations are estimated 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, as per Models [2] and [4] of Table 3

Significance (p-value under a t-test): ***1% level; **5% level; *10% level.

Table 4

Location-level value added and earnings functions: Interactions between human capital and technology use

	(A) Value added function		(B) Earnings function		Wald test p-value
	Without controls (1)	With controls (2)	Without controls (3)	With controls (4)	With controls (5)
Share of workers with university degree	0.618 **	0.554 *	0.032	0.041	0.06
Share of workers trained	-0.047	-0.120	0.081	0.023	0.11
Share of workers using a PC and with:					
Non-university degree and no training on PC	0.462 ***	0.245 **	0.330 ***	0.166 ***	0.42
Non-university degree and training on PC	1.053 ***	0.701 ***	0.589 ***	0.275 ***	0.01
University degree and no training on PC	-0.108	-0.314	0.556 ***	0.259 *	0.05
University degree and training on PC	0.682 **	0.578 *	0.697 ***	0.450 **	0.68
Sample Size	4,219	3,863	4,447	4,070	
R-squared	0.122	0.284	0.176	0.498	

Equations are estimated using nonlinear 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, as per Models [2] and [4] of Table 3. R-squared based on individual regressions.
Significance (p-value under a t-test): ***1% level; **5% level; *10% level.

Table 4A

Location-level value added and earnings functions: Interactions between human capital and technology use

	(A) Value added function		(B) Earnings function		Wald test p-value
	Without controls (1)	With controls (2)	Without controls (3)	With controls (4)	With controls (5)
Share of workers with university degree	0.640 ***	0.578 **	0.040	0.058	0.04
Share of workers trained	-0.032	-0.104	0.079	0.019	0.17
Share of workers using a PC and with:					
Non-university degree and no training on PC	0.459 ***	0.230 **	0.334 ***	0.168 ***	0.52
Non-university degree and classroom training on PC	0.938 ***	0.499 ***	0.726 ***	0.378 ***	0.49
Non-university degree and on-the-job training on PC	0.904 ***	0.672 ***	0.391 ***	0.175	0.00
University degree and no training on PC	-0.133	-0.349	0.548 **	0.246 *	0.04
University degree and classroom training on PC	0.486	0.156	0.520 ***	0.145	0.97
University degree and on-the-job training on PC	0.614 *	0.612 *	0.667 **	0.509 ***	0.73
Sample Size	4,219	3,863	4,447	4,070	
R-squared	0.122	0.283	0.176	0.499	

Equations are estimated using nonlinear 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. R-squared based on individual regressions.
Significance (p-value under a t-test): ***1% level; **5% level; *10% level.