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Estimating the Returns to Firm-Sponsored on-the-Job and Classroom Training

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Abstract:
In this paper, we estimate returns to classroom and on-the-job firm-sponsored training in terms of value-added per worker using longitudinal linked employee-employer Canadian data from 1999 to 2006. We estimate a standard production function controlling for endogenous training decisions because of perceived net benefits and time-varying market conditions using dynamic panel GMM methods. We find that employees who undertook classroom training are 11 percent more productive than otherwise similar employees. We show that returns to on-the-job training are on average lower (3.4 percent). We provide evidence that these lower returns are due to on-the-job training being more closely related to turnover and more geared toward subjects that are less productivity-enhancing.

Keywords: Productivity, Classroom training, On-the-job training, Linked employer-employee data, Turnover, Subjects of training

JEL Classification: C23, D24, J31, J63

1. Introduction

Firms invest considerable resources in training.[1] It is surprising, therefore, that there is no agreement amongst economists as to whether, and to what extent, training has a bearing on firm-level productivity. There are two related reasons for this: data constraints and endogeneity problems. With respect to the former, the chief concerns have been limited information pertaining to training, a dearth of representative longitudinal firm data, and rather imperfect measures of productivity. As to the latter, the endogeneity of training arises from the fact that training is a firm-level decision variable, and factors unobservable to the researcher may be correlated with both training and productivity. This typically takes the form of time-invariant unobserved heterogeneity, such as the quality of management, or of unobserved shocks (say, demand shocks) which have a bearing on both productivity and training.

In this paper, we take a step towards filling this gap. We use longitudinal linked employee-employer data from 1999 to 2006 from Statistics Canada, the Workplace and Employee Survey (WES), to estimate returns to classroom and on-the-job firm-sponsored training in terms of value-added per worker.[2] Since the WES is nationally representative of almost all Canadian businesses, we can reasonably claim that our results are more generalizable than many from other studies.[3] This is in contrast to most of the early literature.[4]

We exploit the structure of our longitudinal data to estimate a standard production function in which the labor input is disaggregated according to training status. There are a number of econometric problems one has to deal with in such an estimation (Zwick (2006)). First, there is the problem of endogenous training decisions. For example, it is possible that workplaces that are more productive for unobserved reasons also offer more training. Second, there could be additional omitted input factors correlated with both training decisions and productivity. Finally, there is the so-called transmission

[1]Heckman, Lochner, and Taber (1998) estimate that more than one half of lifetime human capital is obtained through post-school investment, including training within firms

[2]This is in contrast with such commonly used measures of productivity as workers' wage rates (recent examples include Frazis and Loewenstein (2005) and Goux and Maurin (2000)), or subjective measures such as a supervisor assessment (for example Barron, Black, and Loewenstein (1987) or Bishop (1997)).

[3]Although, as with all survey data, having data at this micro-level introduces some risk of measurement bias, it does enable us to avoid aggregation bias. The latter is something some recent studies (Dearden, Read, and Reenen (2006) for example) are vulnerable to because of their reliance on data aggregated at the industry level.

[4]For example, Holzer, Block, Cheatham, and Knott (1993) use data from only 390 applicants to the Michigan Job Opportunity Bank-Upgrade program from 1987-1989, Bartel (1994) uses data from 495 American firms, and Ballot and Taymaz (2001) have data on only 90 firms in France and 270 firms in Sweden.

bias through which unobserved productivity shocks affect both input choices and output (Griliches and Mairesse (1998)). For example, an unexpected increase in demand might lead a workplace to be more productive while postponing training for future periods.

To take into account endogenous training decisions because of perceived net benefits and time-varying market conditions, we use dynamic panel GMM methods as suggested by Blundell and Bond (2000).[5], [6] Controlling for endogenous training decisions is important. For example, Black and Lynch (2001) do use GMM methods and find no impact of human capital investments on productivity. While ground-breaking, their study is also limited by a small sample size.

Not surprisingly, given the small sample sizes and various empirical strategies used, results have been inconsistent. Two of the most cited studies, Bartel (1994) and Black and Lynch (2001), find no impact of training on productivity or only a deferred impact. Many other studies find a positive impact but the magnitude of the impact is very hard to compare across studies because productivity and/or training are measured very differently (e.g. Ballot and Taymaz (2001) and Holzer, Block, Cheatham, and Knott (1993)). That makes their findings less relevant for policy purposes or even decision making at the firm level.

A number of recent studies have overcome some of these limitations. Dearden, Read, and Reenen (2006) use a long panel data set from the U.K. and although their training measure is aggregated at the industry level, they are able to control for the endogeneity of training in a very general way using GMM methods to find a significant positive effect of training on productivity. In another recent study, Zwick (2006) uses a large panel of German establishments and, correcting for endogeneity using fixed effects and instrumental variables, he finds that increasing the proportion of employees receiving training by 1 percent augment productivity by 0.76 percent. Almeida and Carneiro (2009) use a first-difference IV approach, implemented with a GMM estimator, on a census of Portuguese firms with more than 100 employees. Since they have detailed information on the direct and indirect costs of training, they are able to compute a well-defined rate of return and find that a workplace that does not provide training would obtain negative returns if it were to start investing in training. Conditional on providing training, returns are estimated at 8.6 percent.

[5]These methods have also been used to take into account the endogeneity of input demand decisions.
[6]There are surprisingly few studies that do this. In fact, most of the literature from the 1990s does not attempt to control for the fact that only workplaces which perceive positive net benefits for undertaking training will do so. That is the case for Holzer, Block, Cheatham, and Knott (1993), Bartel (1994), Black and Lynch (1996) and Barrett and O'Connell (2001).

However, these last three studies do not distinguish between on-the-job and classroom training or focus only on formal classroom training. It is important not to focus solely on formal classroom training as some estimates suggest the amount of informal training is about 4-5 times greater than the amount of formal training (Pischke (2005)). Also, it seems equally as important not to aggregate all kinds of training in one single measure because classroom and on-the-job training seem to have different effects on productivity. In the very few studies to make such a distinction, the common finding is that there are positive effects to general (classroom) training but no or negligible effects for specific (on-the-job) training (see Black and Lynch (1996), Barrett and O'Connell (2001) and (Zwick 2005).).

Black and Lynch (1996) find higher returns for off-the-job formal training than for informal training and provide two possible explanations. First, they suggest that classroom *"training outside working hours lowers the output loss associated with on-the-job training"*. Second, they hypothesize that *"those employers that train their workers off the job may be investing in more advanced and time-intensive skills development*." However, they cannot provide any test of the two competing explanations provided.

Barrett and O'Connell (2001), to explain their result, first *"hypothesize that higher spending on specific (on-the-job) training may have arisen in an environment of high staff-turnover, in an effort to maintain productivity levels*". In the end, they reject the hypothesis that turnover is causing the discrepancy in returns but conjecture that employees either are exerting more efforts in formal training (because it is intrinsically more valuable since human capital obtained through formal training is more general in nature and thus also useful in other firms) or that they consider formal training as a gift and respond by increasing their effort level (an argument from the efficiency wage literature).

It should be noted that Barrett and O'Connell (2001)'s conclusion is based in part on the finding that the correlation between net employment changes and levels of training is not significantly different from zero. They use net employment changes because they do not have detailed information on turnover for firms in their sample. A simple computation using our own data set (shown in Table 1) shows statistically significant correlations between both the proportion of employees who received on-the-job training and the proportion who received classroom training, and both the inflow rate (defined as the total number of new hires in the past year divided by end-of-year employment) and the outflow rate (total number of workers who quit the firm in the past year divided by end-of-year employment). This could possibly mean that Barrett and O'Connell (2001) were too quick in dismissing turnover as a potential explanation for the differing returns.[7]

Finally, Zwick (2005) finds that formal external courses have the largest positive impact on productivity, while training on the job has a negative productivity impact. He argues that "*the productivity increasing training forms contain more general human capital content than the other training forms.*". This reconciles his finding with previous studies but it is still not entirely clear why general training should have a greater impact on productivity than specific training.

Using more detailed data than these three previous studies on turnover at the workplace level and information on the subject of training, we argue that both reasons (turnover and the content of training) explain why returns to on-the-job training are lower than those of classroom training.[8]

First, we show that returns to on-the-job training increase markedly as we restrict our sample to low-turnover establishments. Then, comparing training intensities at the workplace level to training intensities from employee samples, we argue that there is a link between turnover and the levels of on-the-job training but no link with levels of classroom training.[9]

However, if high turnover is due to unobserved factors that also affect productivity and training investments negatively (such as a bad working environment), then one needs to rely on an empirical methodology that will take these unobserved factors into account. Using dynamic GMM methods, we, again, find that OLS results underestimate the real impact of on-the-job training. Results show that employees who received classroom training are 11 percent more productive than other employees who did not receive training, while on-the-job training raises productivity by 3.4 percent.[10]

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[7] In fact, it is also hard to reconcile Barrett and O'Connell (2001)'s conclusion with many studies on the determinants of training that provide evidence of a strong link between turnover and the probability of receiving training. One recent example is Frazis, Gittleman, and Joyce (2000) who find a significant negative correlation between turnover and some measures of training incidence. They do not not, however, have any information on the provision of informal training. Booth, Francesconi, and Zoega (2003) also find that higher quit rates translate into a lower incidence of general training.

[8] The fact that turnover and the subject of training are related was recognized by Lynch and Black (1998) who note that *more general types of training are found to be more likely in large establishments and in those with low turnover.*

[9] This agrees with the theoretical model reviewed in Asplund (2005): *Both human capital and internal labor market theories predict a negative relationship between specific training and turnover.* Acemoglu and Pischke (1998) argue that *differing amounts of general training across countries cannot be explained by exogenous differences in turnover alone.*

[10] These last results are estimated somewhat imprecisely: we cannot reject the null hypothesis that returns are the same for both types of training.

These results show that once one takes into account turnover and unobserved factors leading to higher turnover and lower productivity, the difference in returns between classroom and on-the-job training becomes much smaller. However, even if on-the-job training is found to increase productivity on average, returns to classroom training remain higher. We provide evidence that the still higher estimated returns for classroom training are most likely due to subjects that are more productivity enhancing.

In fact, we find that additional on-the-job training linked to higher turnover is not productivity enhancing. The link between turnover and on-the-job training is reflected in the subject of the training received: we find that a large fraction (31) percent of on-the-job training is 'Orientation for new employees' that is not productivity-enhancing. Second, for other (more general) subjects such as 'Sales and marketing training' or 'Computer software', we provide some evidence that returns to on-the-job and classroom training are very close. Finally and most importantly, we find that the subjects of classroom training are more productivity enhancing than the subjects of on-the-job training. This is particularly true in the case of 'Professional training', which is more likely to be the subject of classroom training.

2. Data

We use 1999-2006 data from the Workplace and Employee Survey (WES) conducted by Statistics Canada.[11] The survey is both longitudinal and linked in that it documents the characteristics of workers and workplaces over time.[12] The target population for the workplace component of the survey is defined as the collection of all Canadian establishments with paid employees at the end of March. The sample comes from the "Business Register" of Statistics Canada, which contains information on every business operating in Canada. The survey is therefore nationally representative of Canadian businesses.[13]

The initial 1999 workplace sample is followed over time and is supplemented at two-year intervals with a sample of births selected from units added to the Business Register since the last survey occasion. In 1999, workplace data were collected in person; subsequent workplace surveys were conducted by means of computer assisted telephone interviews. Response rates for each cross-section are typically over 90 percent. In

[11]This is a restricted-access data set available in the Statistics Canada network of Research Data Centers (RDC). Remote access is also possible.

[12]Abowd and Kramarz (1999) classify WES as a survey in which both the sample of workplaces and the sample of workers are cross-sectionally representative of the target population.

[13]Except for establishments located in Yukon, the Northwest Territories and Nunavut and firms operating in fisheries, agriculture and cattle farming.

the case of total non-response, respondents are withdrawn entirely from the survey and sampling weights are recalculated in order to preserve representativeness of the sample.

We use value added as our measure of productivity. It is defined as gross operating revenue minus expenses on intermediary inputs, training expenses and additional labor costs. Labor is measured through the number of employees in the workplace (as of the end of March of the current year).

Measuring capital stock is somewhat more problematic. As with most representative firm-level data, capital stocks for each firm are not available in our data. We treat the capital stock as an omitted (possibly time-varying) variable that could be correlated to training decisions, and use an empirical methodology designed to estimate the causal impact of training on productivity that is robust to this omitted variable.[14]

We compute training intensities in a similar way to previous studies as we have information from the employer part of the survey on the proportion of employees (this measure includes full-time, part-time, permanent and temporary employees) who received on-the-job training and the proportion who received classroom training (in both cases related to their job) in the past year.[15,16] The survey defines classroom training in a very detailed fashion and indicates that all training activities should have the following:

- a pre-determined format, including a pre-defined objective;
- specific content;
- progress that may be monitored and/or evaluated.

However, on-the-job training is only defined as being informal. In 1999, 31 percent of the establishments in the sample offered classroom training and 45 percent offered on-the-job training. Of the workers, 55 percent received either form of training.

It would also be possible to include additional explanatory variables constructed from the employee questionnaires in the linked data. However, information on employees is missing for a non-negligible fraction of the sampled workplaces. Therefore, in most specifications, we use only variables available from the employer questionnaire to get the largest sample size possible. Table 2 presents summary statistics on value added

[14]The survey does provide information on three types of investments made respectively in computer software or hardware, computer-assisted design (CAD) and other machinery or equipment. Our results are robust to incorporating those as additional control variables.

[15]The survey also provides information about the amount of money invested by workplaces. Because of the large proportion of missing values, we unfortunately cannot rely on this information.

[16]As with previous studies, we do not have a measure of the accumulated stock of training.

and number of employees, as well as the distribution of the sample by industry for the initial sample year.

3. Estimating the returns to training from firm-level data

Our basic model is a Cobb-Douglas production function where the dependent variable is value added in workplace j at time t (Q_{jt})

$$\ln Q_{jt} = \beta_L \ln {L^E}_{jt} + \gamma Z_{jt} + \epsilon_{jt}. \tag{3.1}$$

L^E_{jt} is a measure of effective labor, and Z_{jt} includes controls for industry and year. ϵ_{jt} is a residual error term.

Our measure of effective labor $\left(L^E\right)$ depends on the number of employees who received training $\left(L^T\right)$ and the number of employees who did not receive any training $\left(L^{NT}\right)$. Formally, it is defined as

$$\begin{aligned} L^E_{jt} &= \lambda_T L^T_{jt} + \lambda_{NT} L^{NT}_{jt} \\ &= \lambda_{NT} L_{jt} + (\lambda_T - \lambda_{NT}) L^T_{jt} \end{aligned} \tag{3.2}$$

where L is the total number of employees. λ_T (and λ_{NT}) are load factors converting the number of employees who received (and did not receive) training into effective labor. By taking the natural log on each side of equation 3.2, we can approximate L^E_{jt} by

$$\ln L^E_{jt} \approx \ln \lambda_{NT} + \ln L_{jt} + \ln\left(1 + \left(\frac{\lambda_T}{\lambda_{NT}} - 1\right) P_{jt}\right) \tag{3.3}$$

where we define P_{jt} as the proportion of employees who received training.[17] Substituting equation (3.3) in (3.1), we obtain

$$\ln Q_{jt} \approx \beta_0 + \beta_L \ln L_{jt} + \beta_L \kappa P_{jt} + \gamma Z_{jt} + \epsilon_{jt} \tag{3.4}$$

where $\kappa = \left(\frac{\lambda_T}{\lambda_{NT}} - 1\right)$ is the parameter of interest and is interpreted as the relative productivity of an employee who received training compared to an employee who did not.

Results for the estimation of the production function on a year-by-year basis are shown in Table 3. In order to control for the design effect in our estimations, we weight our analysis with the final sampling weights for workplaces as recommended by Statistics Canada. Also, standard errors for all of our coefficient estimates are

[17]The approximation is correct as long as $\frac{L^T}{L}\left(\frac{\lambda_T}{\lambda_{NT}} - 1\right)$ is close to zero. Please see the details in Appendix A.

bootstrapped in order to fully account for the stratified sampling procedure used by Statistics Canada.[18]

Given that in most years, the estimate for β_L is close to 1, we can directly interpret the coefficients on the proportion of employees who received classroom and on-the-job training as the productivity impact of training in terms of value-added. There is substantial variation in the returns to training on a year-by-year basis. Returns to classroom training vary between 7 percent and 28 percent and returns to on-the-job training vary between -14.5 percent and 4.2 percent. However, in all years, returns to classroom training are higher than returns to on-the-job training. In fact, on average, returns to classroom training are 16 percent and returns to on-the-job training -2.6 percent.

It remains to be seen how robust these estimates are when taking into account endogenous training decisions. On the one hand, if firms providing training are self-selected based on the expected returns of training, as would be expected, the numbers given above will be biased upward. On the other hand, turnover might well have the opposite effect, depending on whether high-turnover is associated with low-productivity or whether it is related to shifts in supply in the labor market.

4. Training and turnover

In order to show the impact of labor turnover on the estimates of the returns to training as simply as possible, we estimate our production function for different samples with different turnover rates. This is possible because the WES contains detailed information about the workplace's workforce flows in the previous year. As we restrict our sample to workplaces with low turnover rates, we would expect our estimates of the productivity impact to be less likely to be biased due to labor turnover.

Table 4 presents returns to training for different cut-offs for worker flow rates, both inflow and outflow. To construct the inflow rate, we obtain the total number of new hires in the last year from the workplace questionnaire. To get a hiring rate, we divide by the total number of employees (as of March 31st). To construct the outflow rate, we first compute the total number of workers who separated from the firm in the past year. Separations can be due to resignations, permanent layoffs, dismissal for cause, or retirement. We then also divide by the total number of employees as of March 31st of the current year.

[18]The WES includes detailed information about organizational changes at the workplace level. In principle, this would allow us to explicitly take into account re-organization within the firm that might be correlated with training decisions. However, since incorporating these indicators did not change the estimated impact of training, we do not include them in the results presented below.

It is interesting to note that, as we drop workplaces with high flow rates from the sample, the productivity impact of on-the-job training slowly rises, moving from -0.002 to 0.064 in the last specification in Table 4. Returns to classroom training remain quite stable across all samples. Note also that we stop at a flow rate of 0.3 because sample sizes begin to drop precipitously after that threshold. Again, it is interesting that the patterns are almost identical whether we select the sample based on the inflow or the outflow rate (not shown).

Overall, this is preliminary evidence that the returns to on-the-job training are related to turnover, while the returns to classroom training are not. However, we cannot tell at this point if this is because, as we remove workplaces with high turnover rates, the type of skills associated with on-the-job training become more productivity enhancing; or alternatively, as we move on to smaller samples with lower turnover, the estimated returns to training become less likely to be affected by biases due to job turnover or other omitted variables.

5. Evidence from linked employee samples

Recall that our measure of firm-level training intensities comes from the workplace questionnaire in which the employer has to estimate the number of employees who undertook classroom training or on-the-job training in the past year. In order to assess if the employer's evaluation is correct, we use the fact that we have linked employer-employee data at our disposal to construct alternative measures of training intensities from the sample of employees who were interviewed from each workplace.

For the employee component, the target population is the collection of all employees working, or on paid leave, in the workplace target population. Employees are sampled from an employee list provided by the selected workplaces. For every workplace, a maximum number of 24 employees is selected and for establishments with less than 4 employees, all employees are sampled.

We obtain a sample of 30,563 workplaces for which we are able to construct training intensities in this manner. The total number of observations is lower than the previous sample both because of non-responses from the employee side and because no employees were sampled in 2006.[19] We construct new training intensities by simply counting the number of employees who report having received training in the past year, and dividing

[19] If we restrict our previous sample to exactly the same workplaces, we obtain almost exactly the same point estimates for the productivity impact of classroom and on-the-job training. It is therefore very unlikely that sample selection explains differences between the two sets of results.

by the total number of employees sampled from the workplace. Comparisons of the different training intensities are presented in Table 5.

Since employees who undertook training and separated from the establishment during the past year are obviously not included in the worker sample, but should be taken into account by the manager in the workplace-level survey, it is expected that training intensities computed from the workplace-level survey will be higher. It is indeed the case but only for on-the-job training. Training intensities are much higher (on average 40 percent higher) for on-the-job training in the workplace-level survey than when computed from the worker samples. However, averages for classroom training are almost identical. We interpret this difference as convincing evidence that levels of on-the-job training are much more closely related to labor turnover than levels of classroom training.[20]

It should be noted that on-the-job training intensities should be equal in both samples for workplaces experiencing low turnover (i.e. few separations or few hires). If high turnover is associated with higher levels of on-the-job training and lower productivity, this means that previously estimated returns to on-the-job training will be biased downward.

6. Fixed effects and GMM estimates of the returns to training

The previous section has shown that a meaningful proportion of on-the-job training is linked to turnover at the workplace level. However, it is possible that turnover is due to factors (such as bad management) that are also conducive to lower productivity. We investigate this possibility in detail in this section by using more sophisticated econometric techniques to take into account both fixed and time-varying workplace level variables that could be correlated to both training and productivity.

Remember that a major difficulty with obtaining unbiased estimates of the productivity impact of training (κ) is due to the endogeneity of training decisions (P_{jt}). To illustrate the problem, we decompose the error term into three components as

$$\epsilon_{jt} = \omega_{jt} + \psi_j + \eta_{jt} \tag{6.1}$$

where ω_{jt} are unobserved productivity shocks and ψ_j unobserved firm effects that can both be correlated with the training decisions of the workplace. η_{jt} is the residual

[20]This in contrast to (Barron, Black, and Loewenstein 1997) who report that establishments and workers report a similar incidence of training. But their measures of the incidence at the workplace and worker levels come from different data sets and focus on newly hired workers. Note that we also observe that both establishment and worker measures agree that there is much more on-the-job (informal) training than classroom (formal) training.

error term. If ψ_j is interpreted as the unobserved productivity of the workplace and if more productive workplaces also invest more in training their employees, failure to take this unobserved heterogeneity into account will bias the estimated return to training upward.

ω_{jt} are typically interpreted as unobserved productivity shocks that could be due to demand shocks. For example, it is likely that a workplace that faces an unexpected increase in the demand for its product will temporarily shift more resources away from training to production. Similarly, a workplace facing a temporary downturn in demand for its product might increase training for its employees. If that is the case, unobserved productivity shocks will be negatively correlated to the proportion of employees who received training and estimated returns will be biased downward.

Therefore, it is important to take into account both sources of bias. Moreover, it should be noted that both ordinary least squares and workplace fixed effects methods will lead to biased estimates if both sources of endogeneity are important.

To eliminate unobserved productivity shock, we start by making the assumption (as Blundell and Bond (2000)) that ω_{jt} follows an autoregressive process of order 1 (this assumption will be formally tested in the application):

$$\omega_{jt} = \alpha\omega_{jt-1} + e_{jt} \tag{6.2}$$

with e_{jt} the residual error term. We can then rewrite (3.4) as

$$\begin{aligned} \ln Q_{jt} \quad = \quad & \alpha \ln Q_{jtjt-1} + \beta_L \ln L_{jt} - \alpha\beta_L \ln L_{jt-1} \\ & +\beta_L \kappa P_{jt} - \alpha\beta_L \kappa P_{jt} + \gamma Z_{jt} - \alpha\gamma Z_{jt-1} \\ & +(\psi_j(1-\alpha) + e_{jt} + \eta_{jt} - \alpha\eta_{jt}). \end{aligned} \tag{6.3}$$

Defining $\psi_j^* = \psi_j - \alpha\psi_j$ and $\eta_{jt}^* = \eta_{jt} - \alpha\eta_{jt-1} + e_{jt}$, we can write our final specification as

$$\begin{aligned} \ln Q_{jt} \quad = \quad & \pi_1 \ln Q_{jt-1} + \pi_2 \ln L_{jt} + \pi_3 \ln L_{jt-1} \\ & +\pi_4 P_{jt} + \pi_5 P_{jt-1} + \pi_6 Z_{jt} + \pi_7 Z_{jt-1} + (\psi_j^* + \eta_{jt}^*) \end{aligned} \tag{6.4}$$

subject to the following restrictions

$$\begin{aligned} \pi_3 &= -\pi_2\pi_1 \\ \pi_5 &= -\pi_4\pi_1 \\ \pi_7 &= -\pi_6\pi_1 \end{aligned} \tag{6.5}$$

It should be noted that estimation of (6.4) by OLS will only yield unbiased estimates of the returns to training if there is no endogeneity due to unobserved workplace heterogeneity. However, even in the presence of endogeneity, it is possible, as described by Blundell and Bond (2000), to obtain consistent estimates for (6.4) by using GMM methods.[21] Given consistent estimates of π and $var(\pi)$, we can recover parameter estimates for $(\beta_k, \beta_l, \delta, \alpha)$ by imposing common factor restrictions and using minimum distance methods.

In estimating (6.4), we use lags from 2 on back to create the GMM-type instruments (as described in Arellano and Bond (1991)). First differences of all the exogenous variables are used as standard instruments. As a specification check, we compute the Arellano-Bond test for first– and second-order autocorrelation in the first-differenced errors. In all specifications, we obtain strong evidence against the null hypothesis of zero autocorrelation in the first-differenced errors at order one and find no significant evidence of serial correlation in the first-differenced errors at order 2. Overall, the tests provide no evidence that the model is misspecified.[22]

Results for the estimation of the production function are shown in Table 6. The first column shows OLS results for comparison purposes. Given the close to one estimates for β_L, we compute productivity differentials for classroom and on-the-job training to be 14 percent and 0 percent respectively.[23] This corresponds broadly to the averages we computed from Table 3.

But if firms providing training are self-selected based on the expected returns of training, as would be expected, the numbers given above will be biased upward. Productivity differential estimates obtained using establishment fixed effects will be unbiased as long as the source of endogeneity is fixed over time. As expected, we find a lower estimated coefficient for the impact of classroom training that confirms the previous estimates were biased upward. The estimated productivity differential is down to 7.4 percent.[24] We still find no statistically significant effect for on-the-job training although it should be noted that the estimated productivity impact moves up into positive territory to 2.6 percent.

[21]We prefer this alternative to recent methods suggested by Levinsohn and Petrin (2003) or Olley and Pakes (1996) for example. Those methods assume that the inversion function is non stochastic. If this assumption is violated, estimates will be biased (as argued by Bond and Soderbom (2005), Ackerberg, Caves, and Frazer (2006) and Basu (1999)).

[22]It is possible to compute the Sargan test of overidentifying restriction when using the one-step system estimator. In this case, we cannot reject the null hypothesis that the overidentifying restrictions are valid (Prob. $>$ chi2 $= 0.3830$).

[23]For an estimated parameter $\beta_l = 0.964$.

[24]Given an estimated coefficient for $\beta_l = 0.643$.

The last set of estimates comes from the GMM methods described above. The goal here is to see if the fixed effects estimates are robust to taking into account the possibility that the source of endogeneity is time-varying. Remember that positive demand shocks could lead to both increased productivity and lower training intensity because of limited time opportunities for undertaking training.

The estimated productivity differential for classroom training slowly returns to 11 percent.[25] Interestingly, this last estimated productivity differential is a little bit higher than the previous number obtained using fixed effects. This is to be expected if unobserved productivity shocks are negatively correlated to the workplace's training intensity. However, this last estimate is no longer statistically different from zero. This might be because the instruments are only weakly correlated to the endogenous variables. Still, 11 percent remains the best point estimate for the returns to classroom training.

Interestingly, while the estimated return for on-the-job training stays non-statistically different from zero, the point estimates continue to climb. Taken at face value, the estimated coefficient implies an average productivity differential of 3.4 percent between employees who received on-the-job training and those who did not. The productivity impact of on-the-job training is thus lower than the productivity impact of classroom training. [26]

7. Subjects of training, turnover and productivity

Results from the previous section suggest that on-the-job training is more closely related to turnover than classroom training and that, as a result, returns to on-the-job training are biased downward in simple OLS estimation. However, it appears that even taking into account turnover and unobserved factors leading to higher turnover and lower productivity, returns to classroom training are higher than returns to on-the-job training. In this section, we investigate whether the remaining difference in returns between classroom and on-the-job training could be due to differences in the subject of training and whether these differences can also be linked to turnover. We are able to investigate this possibility further because the WES incorporates detailed information about the subjects of training provided by the workplace.

[25]For $\beta_l = 0.647$.

[26]Note that the coefficient β_L has a more reasonable value in both the FE and GMM specifications. In fact, it is almost identical in both specifications. It does not seem to make a difference whether we treat the stock of capital as a fixed or time-varying omitted variable.

At the employee level, for classroom training, the survey asks about the main subject of the last course taken. In the case of on-the-job training, the survey asks what were the main subjects of the on-the-job training. It is, therefore, possible for on-the-job training to be of many types. At the workplace level, the survey asks if the workplace pays for or provides any of the subjects of training.

At both the employee and workplace levels, the WES distinguishes between thirteen different subjects. Summary statistics on those are provided in Table 7. Comparisons between on-the-job and classroom training are made difficult because of the different ways the questions are framed. However, it is still possible to draw a number of conclusions about the differing content of classroom and on-the-job training.

The main difference between on-the-job and classroom training is that the former is much more likely to be 'Orientation for new employees'. On-the-job training is also more likely to be related to 'Computer hardware' and 'Computer software'. This is true both at the employee and workplace level. The reverse is true for 'Occupational health and safety' and 'Other types of training': these two subjects are more closely related to classroom than on-the-job training.

Table 8 shows similar statistics for low-turnover establishments (those with both inflow and outflow rates below 0.25). It is interesting to note that most classroom training subjects show almost no variation between low- and average-turnover establishment (compared to the incidence shown in Table 7), except for a very small decrease in the incidence of 'Occupation health and safety' training.

However, in the case of on-the-job training, the main difference between low- and average-turnover establishments is that low-turnover workplaces, not surprisingly, provide 'Orientation for new employees' much less frequently. Moreover, we also observe a relative increase in the incidence of on-the-job 'Computer hardware' training for these same low-turnover establishments. It seems, therefore, that as we select establishments with low turnovers, the portfolio of types of on-the-job training moves toward more productivity-enhancing types of training. However, even among these low turnover establishments, 7 percent of employees report receiving 'Orientation for new employees' type of training. This seems to imply that there is still a meaningful proportion of non-productivity-enhancing training taking place in these workplaces.

In order to test this hypothesis a little bit more formally, we again estimated the econometric specification in equation 3.4, taking into account the subjects of training offered by the workplace.[27] Estimation results, presented in Table 9, generally agree with the previously stated hypotheses.

The first result to notice is that returns to classroom and on-the-job training are much closer (5.3 percent versus −0.8 percent) compared to the averages from Table 3 (16 percent versus −2.6 percent). The second is that, while many types of training seem to have no statistically significant impact on productivity, when there are statistically significant coefficients, results are as expected. More importantly, this is the case with 'Orientation for new employees' on-the-job training that has a significant negative impact on productivity. Quite interestingly, some types of training ('Sales and marketing training' and 'Computer software') have a significant positive impact on productivity for both classroom and on-the-job training. Moreover, the magnitude of the impact is similar for both classroom and on-the-job training. Some other types of training have a statistically significant impact on productivity only in the case of classroom training ('Team building...' and 'Occupation health...').

In light of these results, and remembering the two greatest differences in the incidence of types of training at the employee level, namely that employees receiving on-the-job training were seven times more likely to undertake 'Orientation for new employees', and that employees receiving classroom training were twice as likely to undertake 'Occupation health...' training, we conclude that the subjects of training explain a non-trivial part of the difference in returns between on-the-job and classroom training. However, we are the first to admit that this is a very imperfect measure of the returns to subjects of training. In the next section, we return to the employee sample to shed more light on how subjects of training influence productivity.

8. More evidence on subjects of training and productivity using the employee samples

Computing training intensity from the worker questionnaire is also useful because it allows us to characterize in a more precise way the human capital investments of the workplace. This is because training intensities computed from the workplace questionnaire do not take into account the fact that a sizable fraction of workers take part in both on-the-job and classroom training. Our aim in this section is to investigate

[27] At the workplace level, we have no way to disaggregate the number of employees who received training into its different types. It could be possible to build these disaggregated proportions from the worker questionnaire but still, the aggregation problem is made more difficult by the following: (1) on-the-job training can be of many types, and (2) we only know the subject of the classroom training course.

whether the subjects of training differed between employees who received either on-the-job or classroom training, and those who received both. Estimating returns to the three types of training, we are then able to indirectly draw conclusions about the different impact on productivity of the subjects of training.

Table 10 compares the training subjects received by employees who did both on-the-job and classroom training and those received by employees who did only one or the other. Employees who received only on-the-job training are 50 percent more likely to undertake 'Orientation for new employees' and less likely to do 'Professional training', 'Group decision making' and 'Team building'.

Thus, we estimate two additional specifications for the production function with training intensities computed from the worker sample. In the first specification, we merge classroom and on-the-job training and look at the productivity impact of receiving training whatever its type. In the second specification, we construct three different measures of training, distinguishing among workers who received both types of training, only classroom or only on-the-job training. Results from these two specifications are shown in Table 11. To be sure that our results are not biased because of worker attrition, note that we only use years in which workers were sampled.

If the returns to on-the-job training are really zero, the coefficient for the proportion of workers who took part in both types of training should be equal to the coefficient for the proportion of workers who received only classroom training. This is apparently not the case: the null hypothesis that the coefficients are equal is rejected at the 10 percent level. In fact, the difference between the two coefficients constitutes one estimate of the productivity impact of on-the-job training. Calculating that difference yields a productivity increase due to the-job training of 12.5 percent. Returns for employees who only received classroom training stand at more than 22 percent. While this is higher than what we estimated using training intensities computed from the workplace-level survey, the two numbers are not statistically different.[28]

Overall, these results seem to indicate that there are two types of on-the-job training. The first type is more closely related to turnover with a weak impact on productivity being picked up by the non-statistically significant coefficient on the proportion of workers who received only on-the-job training in Table 11. The second type of on-the-job training is less related to job turnover and is also more likely to be accompanied by

[28]It would be interesting to see how these numbers vary using more sophisticated statistical methods taking into account endogenous training decisions. However, WES selects new employees in odd years and an appropriate statistical model would have to take worker attrition in even years into account. Therefore, we focus on results using the workplace-level data in the remainder of the paper.

complementary classroom training. In terms of subjects of training, again this seems to imply that ‘Orientation for new employees’ is not productivity-enhancing while subjects like ‘Professional training’, ‘Group decision making’ and ’Team building’ are more productivity-enhancing. These subjects are more closely linked to classroom training, probably because they are more easily taught in a classroom setting.

9. Conclusion

In this article, we estimate returns to on-the-job and classroom training on value-added per worker using linked longitudinal employee-employer Canadian data from 1999 to 2006. We control for endogenous training decisions because of perceived net benefits and time-varying market conditions. Our estimates show that employees who received classroom training are 11 percent more productive than other employees who did not receive training. We find that not all on-job-training is productivity-enhancing. On average, returns to on-the-job training stand at 3.4 percent but can be as high as returns to classroom training once the impact of labor turnover has been removed. We find that a large fraction of on-the-job training ‘Orientation for new employees’ is not productivity-enhancing. However, most importantly, we find that the subjects of classroom training are more productivity-enhancing than the subjects of on-the-job training. This is particularly the case for ‘Professional training’, which is more likely to be the subject of classroom training.

Given the estimated productivity differential between trained and untrained employees, it is possible to attempt computing the returns on the establishment investment in classroom training. For an average amount of value added per employee at $77.712 in our sample, the 11 percent productivity gain yields approximately $8000 in additional value added per trained employee per year. This is certainly an upper bound on the returns to classroom training expenses since it assumes that the employee is linked to the firm for the whole year. WES provides some information on costs in the case of classroom training for a subset of workplaces with average classroom training expenses per (trained) employee being approximately $1000. This would mean that each 1$ invested in classroom training yields a maximum of 8$ in value added. It would be interesting to know how this yield is divided between the worker and the workplace and whether the provided costs are representative, whether they include all relevant costs and how job turnover affects the expected return.

While we find lower returns for on-the-job than classroom training, it is possible that on-the-job training has a greater impact on alternative measures of workplace performance. It would be interesting to further investigate whether this is the case for the performance of the workplace in terms of innovation or product quality for example. Also, it is unlikely that the human capital investments policy of the workplace is independent of its decisions with respect to its investments in software, hardware or machinery and equipment. Many authors provide evidence of complementarities in terms of their impact on productivity between human and physical capital investments (see for example Bresnahan, Brynjolfsson, and Hitt (2002)). It would be interesting to explore whether such complementarities are stronger in the case of on-the-job rather than classroom training.

References

Abowd, J. M. and F. Kramarz (1999). The analysis of labor markets using matched employer-employee data. In O. Ashenfelter and D. Card (Eds.), *Handbook of Labor Economics, vol 3B*, Chapter 40, pp. 2629–2710. Elsevier Science North Holland.

Acemoglu, D. and J. Pischke (1998). Why do firms train? Theory and evidence. *Quarterly Journal of Economics 113*(1), 79–118.

Ackerberg, D., K. Caves, and G. Frazer (2006). Structural identification of production functions. Working paper, University of Arizona, UCLA and University of Toronto.

Almeida, R. and P. Carneiro (2009). The return to firm investments in human capital. *Labour Economics 16*(1), 97–106.

Arellano, M. and S. Bond (1991). Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. *Review of Economic Studies 58*, 277–297.

Asplund, R. (2005). The provision and effects of company training: A brief review of the literature. *Nordic Journal of Political Economy 2*(5), 47–73.

Ballot, G. F. and E. F. Taymaz (2001). Firm's human capital, R&D and performance: A study on French and Swedish firms. *Labour Economics 8*(4), 443–462.

Barrett, A. and P. O'Connell (2001). Does training generally work? The return to in-company training. *Industrial and Labor Relations Review 54*(3), 647–663.

Barron, J. M., D. A. Black, and M. A. Loewenstein (1987). Employer size: The implications for search, training, capital investments, starting wages, and wage growth. *Journal of Labor Economics 7*(1), 1–19.

Barron, J. M., D. A. Black, and M. A. Loewenstein (1997). How well do we measure training? *Journal of Labor Economics 15*, 507–528.

Bartel, A. P. (1994). Productivity gains from the implementation of employee training programs. *Industrial Relations 33*(4), 411–425.

Basu, S. (1999). Discussion on "Estimating production function using intermediate inputs to control for unobservables" by A. Petrin and J. Levinsohn. Working paper, NBER Productivity Program Meeting.

Bishop, J. H. (1997). What we know about employer-provided training: A review of the literature. In S. W. Polachek (Ed.), *Research in Labor Economics*, Volume 11, pp. 19–87. JAI Press, Greenwich, Conn.

Black, S. and L. Lynch (1996). Human-capital investments and productivity. *American Economic Review Papers and Proceedings 82*(2), 263–267.

Black, S. E. and L. M. Lynch (2001). How to compete: The impact of workplace practices and information technology on productivity. *Review of Economics and Statistics 82*(1), 434–445.

Blundell, R. and S. Bond (2000). GMM estimation with persistent panel data: An application to production functions. *Econometric Reviews 19*(3), 321–340.

Bond, S. and M. Soderbom (2005). Adjustment costs and the identification of Cobb-Douglas production functions. Working Paper 05/04, Institute for Fiscal Studies.

Booth, A., M. Francesconi, and G. Zoega (2003). Unions, work-related training, and wages: Evidence for British men. *Industrial and Labor Relations Review 57*, 68.

Bresnahan, T. F., E. Brynjolfsson, and L. M. Hitt (2002). Information technology, workplace organization and the demand for skilled labor: Firm level evidence. *Quarterly Journal of Economics 117*(1), 339–376.

Dearden, L., H. Read, and J. V. Reenen (2006). The impact of training on productivity and wages: Evidence from British panel data. *Oxford Bulletin of Economic and Social Research 68*(4), 397–421.

Frazis, H., M. Gittleman, and M. Joyce (2000). Correlates of training: An analysis using both employer and employee characteristics. *Industrial and Labor Relations Review 53*(3), 443–463.

Frazis, H. and M. A. Loewenstein (2005). Reexamining the returns to training: Functional form, magnitude, and interpretation. *Journal of Human Resources 40*(2), 453–476.

Goux, D. and E. Maurin (2000). Returns to firm-provided training: Evidence from French worker-firm matched data. *Labour Economics 7*(1-19).

Griliches, Z. and J. Mairesse (1998). Production functions: The search for identification. In S. Strom (Ed.), *Econometrics and Economic Theory in the Twentieth Century: The Ragnar Frisch Centennial Symposium*, pp. 169–203. Cambridge University Press.

Heckman, J., L. Lochner, and C. Taber (1998, May). Tax policy and human-capital formation. *The American Economic Review 88*(2), 293–297.

Holzer, H., R. Block, M. Cheatham, and J. Knott (1993). Are training subsidies for firms effective? the Michigan experience. *Industrial and Labor Relations Review 46*(4), 625–636.

Levinsohn, J. and A. Petrin (2003). Estimating production function using inputs to control for unobservables. *Review of Economic Studies 70*(2), 317–342.

Lynch, L. M. and S. E. Black (1998). Beyond the incidence of employer provided training. *Industrial and Labor Relations Review 52*(1), 64–81.

Olley, G. and A. Pakes (1996). The dynamics of productivity in the telecommunications equipment industry. *Econometrica 64*, 1263–1297.

Pischke, J.-S. (2005). Comments on "Workplace training in Europe" by Bassanini et al. *fRDB Conference Paper on Education and Training in Europe - London School of Economics*.

Zwick, T. (2005). Continuing vocational training forms and establishment productivity in Germany. *German Economic Review 6*(2), 155–184.

Zwick, T. (2006). The impact of training intensity on establishment productivity. *Industrial Relations 45*(1), 26–46.

Appendix A. Detailed derivation of the statistical model

Let L^E be the number of effective units of labor, L^T the number of employees who received classroom training in the past year, and L^{NT} the number of employees who did not receive classroom training. The total number of employees L is given by

$$L = L^{NT} + L^T,$$

and the total number of effective units of labor is given by

$$L^E = \lambda_{NT} L^{NT} + \lambda_T L^T$$

Then, we can rewrite the above equation as

$$\begin{aligned}
L^E &= \lambda_{NT} L^{NT} + \lambda_T L^T + (\lambda_{NT} L^T - \lambda_{NT} L^T) \\
&= \lambda_{NT}(L^{NT} + L^T) + (\lambda_T - \lambda_{NT}) L^T \\
&= \lambda_{NT} L + (\lambda_T - \lambda_{NT}) L^T \\
&= \lambda_{NT} L + \lambda_T L^T + \lambda_{NT} L^T \\
&= \lambda_{NT} L \left(1 + \frac{\lambda_T}{\lambda_{NT}} \frac{L^T}{L} - \frac{L_T}{L}\right) \\
&= \lambda_{NT} L \left(1 + \frac{L^T}{L}\left(\frac{\lambda_T}{\lambda_{NT}} - 1\right)\right).
\end{aligned}$$

Taking logs on both sides, we get the following approximation:

$$\ln L^E \approx \ln \lambda_{NT} + \ln L + \left(\frac{L^T}{L}\left(\frac{\lambda_T}{\lambda_{NT}} - 1\right)\right).$$

The approximation holds as long as $\frac{L^T}{L}\left(\frac{\lambda_T}{\lambda_{NT}} - 1\right)$ is close to zero. Defining the proportion of workers who received classroom training in the past year as P^T, we finally obtain

$$\ln L^E \approx \text{constant} + \ln L + \kappa P^T$$

where $\kappa = \left(\frac{\lambda_T}{\lambda_{NT}} - 1\right)$ is interpreted as the returns to training in percentage. It is positive if employees who received classroom training contribute more effective units of labor than employees who did not receive classroom training and negative otherwise.

Appendix B. Tables

Table 1. Correlation matrix (at workplace level)

	inflow	outflow	prop. cls	prop. otj
inflow	1.00			
outflow	0.63***	1.00		
prop. cls	0.14***	0.09 ***	1.00	
prop. otj	0.23***	0.22***	0.41***	1.00

*** significant at 1%

Table 2. Summary statistics - 1999

Variable	Mean	Std Dev.
ln(Value added)	12.434	1.503
ln(L)	1.737	1.168
Industry		
Labour tertiary	.030	.170
Primary manufacturing	.012	.107
Secondary manufacturing	.018	.133
Capital tertiary	.024	.154
Construction	.076	.265
Transport	.110	.313
Communication	.014	.116
Retail	.331	.471
Finance and insurance	.050	.219
Real estate	.040	.193
Business services	.125	.331
Education and health care	.134	.341
Information and culture	.022	.145

N = 5,072

Table 3. Coefficient estimates - production function

	1999	2000	2001	2002	2003	2004	2005	2006
ln(# employees)	1.014***	0.984***	0.961***	0.957***	0.942***	0.929***	0.946***	0.973***
	(0.026)	(0.026)	(0.025)	(0.024)	(0.023)	(0.021)	(0.020)	(0.020)
prop - classroom	0.283***	0.142	0.072	0.165*	0.078*	0.225***	0.137***	0.175**
	(0.087)	(0.134)	(0.047)	(0.091)	(0.043)	(0.063)	(0.050)	(0.073)
prop - on-the-job	-0.145*	-0.023	-0.015	0.004	0.042	-0.033	-0.000	-0.035
	(0.081)	(0.042)	(0.032)	(0.040)	(0.052)	(0.042)	(0.052)	(0.055)
# observations	5,072	4,952	5,220	4,719	5,484	5,120	5,664	5,332
R-squared	0.59	0.57	0.58	0.59	0.58	0.62	0.63	0.64

Includes controls for industry (14) and year (8)
Bootstrapped standard errors in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 4. Coefficient estimates - production function for different turnover rates (flows)

	FL<=1	FL<=.9	FL<=.8	FL<.7	FL<.6	FL<.5	FL<.4	FL<.3
ln(# employees)	0.968***	0.978***	0.979***	0.980***	0.978***	0.980***	0.981***	0.974***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.011)	(0.011)
prop - classroom	0.184***	0.170***	0.170***	0.168***	0.172***	0.159***	0.198***	0.181***
	(0.042)	(0.044)	(0.044)	(0.045)	(0.042)	(0.041)	(0.049)	(0.053)
prop - on-the-job	0.000	0.012	0.017	0.025	0.040	0.049	0.055*	0.064*
	(0.026)	(0.028)	(0.028)	(0.028)	(0.028)	(0.030)	(0.032)	(0.035)
# observations	38,684	37,274	36,624	35,825	34,465	33,236	29,898	25,964
R-squared	0.60	0.60	0.61	0.61	0.61	0.61	0.62	0.62

Includes controls for industry (14) and year (8)

Bootstrapped standard errors in parentheses

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 5. Training intensities

	1999	2000	2001	2002	2003	2004	2005	99-05
From employer questionnaire (er)								
Classroom	0.18	0.21	0.21	0.21	0.23	0.24	0.22	0.21
On-the-job	0.30	0.29	0.34	0.33	0.35	0.34	0.34	0.33
From employee questionnaires (ee)								
Classroom	0.22	0.20	0.21	0.17	0.23	0.21	0.21	0.21
On-the-job	0.23	0.21	0.26	0.20	0.26	0.21	0.27	0.23
Ratio er/ee								
Classroom	0.82	1.05	1.00	1.24	1.00	1.14	1.05	1.00
On-the-job	1.30	1.38	1.31	1.65	1.35	1.62	1.26	1.43
# observations	4,590	4,433	4,413	3,919	4,413	3,996	4,799	30,563

Table 6. Coefficient estimates - production function

	OLS	FE	B&B
ln(# employees)	0.964***	0.643***	0.647***
	(0.009)	(0.029)	(0.118)
prop - classroom	0.142***	0.048***	0.072
	(0.029)	(0.018)	(0.058)
prop - on-the-job	-0.009	0.017	0.022
	(0.019)	(0.014)	(0.043)
# observations	41,563	41,563	32,761
R-squared	0.60	0.87	-
# workplaces	8,270	8,270	7,555

Inc. controls for industries (14) and year (8)
Bootstrapped standard errors in parentheses
* significant at 10%; ** at 5%; *** at 1%

Table 7. Summary statistics - Types of training

	Employee		Workplace	
	CLS	OTJ	CLS	OTJ
Orientation for new employees	1	9	12	31
Managerial/supervisory training	6	8	9	10
Professional training	17	20	12	9
Apprenticeship training	1	4	6	9
Sales and marketing training	5	8	9	12
Computer hardware	2	5	5	7
Computer software	15	27	12	18
Other office and non-office equipment	2	7	3	6
Group decision making and problem solving	1	4	4	5
Team building, leadership, communication	3	6	7	9
Occupation health and safety, environmental protection	17	11	11	12
Literacy or numeracy	0	1	1	1
Other	29	24	6	5
Total	99%	134%	97%	134%

TABLE 8. Types of training for low-turnover establishments

	Employee		Workplace	
	CLS	OTJ	CLS	OTJ
Orientation for new employees	1	7	10	22
Managerial/supervisory training	6	8	8	8
Professional training	19	21	12	8
Apprenticeship training	1	4	6	8
Sales and marketing training	5	8	9	9
Computer hardware	2	5	5	7
Computer software	18	30	12	16
Other office and non-office equipment	2	7	3	5
Group decision making and problem solving	1	5	4	4
Team building, leadership, communication	3	7	7	7
Occupation health and safety, environmental protection	15	12	10	10
Literacy or numeracy	0	1	1	1
Other	28	23	5	4
Total	101	138	92	109

Selected establishments have inflow and outflow rates below 0.25

TABLE 9. Coefficient estimates - Production function with types of training as additional covariates

	CLS	OTJ
ln(# employees)	0.926***	
	(0.011)	
prop - training	0.053***	-0.008
	(0.020)	(0.018)
Types of training		
Orientation for new employees	-0.044	-0.121***
	(0.058)	(0.034)
Managerial/supervisory training	0.060	0.037
	(0.039)	(0.042)
Professional training	0.066**	-0.028
	(0.033)	(0.038)
Apprenticeship training	-0.056	0.014
	(0.045)	(0.038)
Sales and marketing training	0.149***	0.125***
	(0.048)	(0.045)
Computer hardware	0.026	-0.006
	(0.052)	(0.054)
Computer software	0.163***	0.152***
	(0.038)	(0.039)
Other office and non-office equipment	-0.072	0.005
	(0.053)	(0.053)
Group decision making and problem solving	-0.092	-0.246***
	(0.057)	(0.054)
Team building, leadership, communication	0.156***	0.037
	(0.056)	(0.053)
Occupation health and safety, environmental protection	0.145***	0.042
	(0.034)	(0.034)
Literacy or numeracy	-0.119	-0.084
	(0.103)	(0.093)
Other	-0.094*	-0.036
	(0.054)	(0.046)
# observations	41,563	
R-squared	0.61	
# workplaces	8,270	

Inc. controls for industries (14) and year (8)
Bootstrapped standard errors in parentheses
* significant at 10%; ** at 5%; *** at 1%

Table 10. Differences in types of training received by employees who received both classroom and on-the-job training and employees who received one or the other

	BOTH		ONLY	
	CLS	OTJ	CLS	OTJ
Orientation for new employees	1	7	1	10
Managerial/supervisory training	7	9	6	8
Professional training	20	23	17	17
Apprenticeship training	1	3	1	3
Sales and marketing training	6	9	5	8
Computer hardware	2	5	2	5
Computer software	18	27	16	27
Other office and non-office equipment	2	7	2	7
Group decision making and problem solving	1	6	1	4
Team building, leadership, communication	3	8	3	5
Occupation health and safety, environmental protection	13	11	16	11
Literacy or numeracy	0	1	0	1
Other	25	24	29	24
Total	99	140	99	130

TABLE 11. Coefficient estimates - production function with training intensities computed from worker samples

	99,01,03,05	99,01,03,05
ln(# employees)	0.974***	0.968***
	(0.013)	(0.013)
prop - any	0.124**	
	(0.050)	
prop - both		0.350***
		(0.095)
prop - only cls		0.229***
		(0.066)
prop - only otj		-0.048
		(0.068)
# observations	18215	18215
R-squared	0.59	0.59

Inc. controls for industries (14) and year (8)
Bootstrapped standard errors in parentheses
* significant at 10%; ** at 5%; *** at 1%