Are there any returns to firm-sponsored training? Productivity and beyond.*

Benoit Dostie[†]

April 7th 2008

Abstract

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 2004. We control for endogenous training decisions because of perceived net benefits and market conditions. In addition, we also investigate whether workplaces that invest more in training their employees obtain benefits in terms of innovation, unit production costs, sales growth, product quality, customer satisfaction and profitability.

1 Introduction

Firms as well as governments invest considerable resources in training. 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

*PRELIMINARY AND INCOMPLETE. DO NOT QUOTE.

†Corresponding author: Institute of Applied Economics, HEC Montréal, University of Montréal, Montréal (Québec), H3T 2A7 ; IZA, CIRANO, CIRPÉE; benoit.dostie@hec.ca

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 simultaneity in the form 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. Our analysis is useful for at least two reasons. First, our data include a more precise and objective measure of productivity than has been available to most other studies, namely value added. This is in contrast with such commonly used measures as workers' wage rates[1], which capture individual rather than firm-level productivity, sales or revenues[2] which may reflect demand rather than productivity increases, or subjective measures such as a supervisor assessment.[3] Moreover our key variables (training and productivity measures in particular) are at the workplace level. 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 that both seminal works (eg: Bartel (1994)) as well as recent recent studies (eg:Dearden, Read, and Reenen (2006)) are vulerable to because of their reliance on data aggregated at the industry-level.

Second, we exploit our longitudinal data structure to control for endogenous training decision driven by perceived net benefits and time-varying market conditions. There are few studies which do this. Black and Lynch (2001) use partially-panel U.S. data from two points in time and significant effects of train-

[1] Recent examples include Frazis and Loewenstein (2005) and Goux and Maurin (2000)
[2] For example Black and Lynch (1996)
[3] For example Barron, Black, and Loewenstein (1987) or Bishop (1997).

ing on productivity in the cross-section disappeared in their firm fixed effects estimations. While ground-breaking, their study is limited by small sample size, high attrition and the partial-panel nature. Ichinowski et al (1997) in an earlier study examine plant-level data for a panel of US steel finishing mills. Conrtolling for plant fixed effects, the find that training only matters in combination with compelementary human resource practices. Their study, while rich in detail, has the limitation that its results are not easily generalizable.

A number of recent studies have overcome some of these limitations. Dearden, Read, and Reenen (2006) use a long panel dataset from the U.K. and although their training measure is aggregated at the indusry level, they are able to control for the endogeneity of training using GMM meethods to find a significant positive effect of training on productivity. In a recent study Zwick (2006) uses a large panel of German and correcting for endogeneity using fixed effects and instrumental variables, he finds that increasing the proportion of employees receiving training by 1% augment productivity by 0.76%. Almeida and Carneiro (2006) use a first-difference IV approach for a large panel Portuguese firms 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 24%.

Our paper adds to this recent panel data literature on several counts. Like many of these studies, our panel is reasonably long – we use 6 years of data (1999-2004) – and our data are are nationally representative. We also make two additional contibutions. First, we estimate returns to both on-the-job and classroom training on value-added per worker.[4] Second, we look beyond productivity gains by investigating whether workplaces that invest more in training their employees obtain benefits in terms of innovation, unit production costs,

[4] And here, we improve on Dostie and Pelletier (2007) by controlling for endogenous training decisions.

sales growth, product quality, customer satisfaction and profitability.

2 Data

Our data come from the Workplace and Employee Survey (WES) conducted by Statistics Canada.[5] WES has been conducted annually since 1999 and we use all 6 years of available data (1999-2004). The survey is both longitudinal and linked in that it documents the characteristics of workers and workplaces over time.[6] The target population for the workplace component of the survey is defined as the collection of all Canadian establishments who paid employees in March of the year of the survey. 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, except for those located in Yukon, the Northwest Territories and Nunavut and firms operating in fisheries, agriculture and cattle farming.

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. Response rates for each cross-section are typically over 90 per cent. In 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.

WES selects new employees in odd years. For workplaces, the initial 1999 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

[5]This is a restricted-access data set available in Statistics Canada Research Data Centers (RDC).

[6]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.

last survey occasion. In order to control for the design effect in our estimations, we weighted our analysis with the final sampling weights for workplaces as recommended by Statistics Canada.

In 1999, workplace data were collected in person; subsequent workplace surveys were conducted by means of computer assisted telephone interviews. For the employee component, telephone interviews were conducted with individuals who had agreed to participate in the survey by filling out and posting an employee participation form.

We have a relatively precise measure of workplace productivity (our dependent variable) in value added, defined as gross operating revenue minus expenses on materials, training and non-wage benefits. Labor is measured through the number of employees in the workplace. Our measure of capital stock is somewhat more problematic. As with most firm-level data, capital stocks for each firm are not available in our data. We therefore proxy the capital stock by taking the stock of the 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 (see Dostie and Pelletier (2007) and Turcotte and Rennison (2004)). [7]

A second important performance measure is innovation. With respect to innovation, the WES asks: "Between April 1 [of the previous year] and March 31 [of the current year], has this workplace introduced (i) new products or services, (ii) improved products or services, (iii) new processes, (iv) improved processes?", with detailed descriptions of what is meant by new and improved products and processes.

Our other measures of performance are subjective. For each of (A) Unit production costs (including the production of service), (B) Productivity, (C) Sales

[7] Although this measure is admittedly imperfect, findings pertaining to our main variables of interest are robust to alternative proxies as well as the exclusion of the capital stock variable.

growth, (D) Product quality, (E) Customer satisfaction and (F) Profitability, we have information on whether the performance of the workplace has increased, remained the same or decreased in the past year. It is quite interesting to note that we have both objective and subjective measures of productivity.

The use of subjective measures is often criticized for lack of comparability across firms or across time within firms. Therefore, results for this part of the analysis should be interpreted with caution and as indicative only of likely impacts of training beyond productivity.

Finally, we use similar measures of the intensity of training as previous studies as we have information on the proportion of employee that received on-the-job training and the proportion that received classroom training in the past year.[8]

3 Empirical Strategy

3.1 Returns to value added per worker

Our basic model is a Cobb-Douglas production function where the dependent variable is value added in workplace j at time t (Q_{jt})[9]

$$\ln Q_{jt} = \beta_L \ln L^E{}_{jt} + \beta_K \ln K_{jt} + \gamma Z_{jt} + \epsilon_{jt}. \quad (1)$$

L^E_{jt} is a measure of effective labor, K_{jt} is capital stock and Z_{jt} includes controls for industry, year, organisational practices and other aspects of the workforce like the proportion of employees covered by a collective bargaining agreement. Summary statistics on Z are presented in Table 1. ϵ_{jt} is a residual error term.

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

[9] We measure value-added as the difference between gross revenues and expenses on intermediary inputs. We also substract training expenses as well as additional labor costs.

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

$$L_{jt}^{E} = \lambda_T L_{jt}^T + \lambda_{NT} L_{jt}^{NT} = \lambda_{NT} L_{jt} + (\lambda_T - \lambda_{NT}) L_{jt}^T \tag{2}$$

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. Equation (2) can be rewritten as

$$\ln L_{jt}^{A} = \ln \lambda_{NF} + \ln L_{jt} + \ln \left(1 + \left(\frac{\lambda_F}{\lambda_{NF}} - 1\right) P_{jt}\right) \tag{3}$$

where we define P_{jt} as the proportion of employees who received training. Substitutin equation (3) in (1), we obtain

$$\ln Q_{jt} \simeq \beta_0 + \beta_L \ln L_{jt} + \beta_K \ln K_{jt} + \beta_L \kappa P_{jt} + \gamma Z_{jt} + \epsilon_{jt} \tag{4}$$

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

A major difficulty with obtaining unbiased estimates of κ is due to the endogeneity of P_{jt}. To illustrate the problem, we decompose the error term into three components as

$$\epsilon_{jt} = \omega_{jt} + \psi_j + \eta_{jt} \tag{5}$$

where ω_{jt} is an unobserved productivity shocks and ψ_j an unobserved firm effects that can both be correlated with the training decisions of the workplace. η_{jt} is the residual 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 exemple, it is likely that a workplace that face an unexpected increase in the demande for its product will temporarily more ressources aways from training to production. Likewise, 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 recevied training and estimated returns will be biased downward.

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

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

$$\omega_{jt} = \alpha\omega_{jt-1} + e_{jt} \tag{6}$$

with e_{jt} the residual error term. We can then rewrite (4) as

$$\begin{aligned} \ln Q_{jt} \quad = \quad & \alpha \ln Q_{jtjt-1} + \beta_K \ln K_{jt} - \alpha\beta_K \ln K_{jt-1} + \beta_L \ln L_{jt} - \alpha\beta_L L_{jt-1} \\ & + \beta_L \kappa P_{jt} - \alpha\beta_L \kappa P_{jt} + \gamma Z_{jt} - \alpha\gamma Z_{jt-1} \\ & + (\psi_j(1-\alpha) + e_{jt} + \eta_{jt} - \alpha\eta_{jt}) \end{aligned} \tag{7}$$

or

$$
\begin{aligned}
\ln Q_{jt} \quad = \quad & \pi_1 \ln Q_{jt-1} + \pi_2 K_{jt} + \pi_3 K_{jt-1} + \pi_4 L_{jt} + \pi_5 L_{jt-1} + \\
& + \pi_6 P_{jt} + \pi_7 P_{jt-1} + \pi_8 Z_{jt} + \pi_9 Z_{jt-1} + \gamma_t^* + (\psi_j^* + \eta_{jt}^*) \qquad (8)
\end{aligned}
$$

subject to the following restrictions

$$
\begin{aligned}
\pi_3 &= -\pi_2 \pi_1 \\
\pi_5 &= -\pi_4 \pi_1 \\
\pi_7 &= -\pi_6 \pi_1 \\
\pi_9 &= -\pi_8 \pi_1 \qquad (9)
\end{aligned}
$$

It should be noted that estimation of (8) by OLS will yield unbiased estimates of the returns to training if there is no endogeneity due to unobserved workplace heterogeneity. Since this is not likely to be the case, we estimate it by GMM methods as suggested by Blundell and Bond (1999).

It is possible, as described by Blundell and Bond (1999), to obtain consistent estimates for (8) by using GMM methods.[10] Given consistents estimates of π and $var\left(\pi\right)$, we can recover parameters estimates for $(\beta_k, \beta_l, \delta, \alpha)$ by imposing common factor restrictions and using minimum distance. and use system GMM methods to obtain coefficient estimates.

In estimating (8), we use lags from 2 on back to create the GGM-type instruments (as described in Arellano and Bond (1991)). First difference of all the exogenous variables were used as standard instruments. As a specification check, we compute the Arellano-Bond test for first− and second-order autocorrelation

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

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 test provide no evidence that the model is misspecified.

One potential problem with the use of Blundell and Bond (1999)'s method is that, for example, Gorodnichenko (2006) shows that the Blundell and Bond estimator is in general weakly identified. However, we do not notice any identification problems with the coefficient estimates obtained through system GMM estimation. This is most likely due to the large size of our sample with some workplaces observed for as long as five years.

3.2 Productivity and beyond

To estimated the returns to training on other performance measure for the workplace, we have to use a different methodology since performance in this case is measured as a limited dependent variable. Recall that we have information on six performance measures: A) Unit production costs (including the production of service), (B) Productivity, (C) Sales growth, (D) Product quality, (E) Customer satisfaction and (F) Profitability, and know whether performance has improved in the last year, stayed the same, or decreased.

Let $\widetilde{y}_{it}$ be an unobserved performance measure. For example, $\widetilde{y}_{it}$ could be interpreted as an index of product quality (D) or profits in dollars (F). We assume a linear model for $\widetilde{y}_{it}$ with a similar set of explanatory variables as previously:

$$\begin{aligned}\widetilde{y}_{jt} &= \delta_0 + \delta_L \ln L_{jt} + \delta_K \ln K_{jt} + \delta_P P_{jt} + \gamma Z_{jt} + \epsilon_{jt} && (10)\\ &= \beta X_{it} + \epsilon_{jt} && (11)\end{aligned}$$

Assuming ϵ_{jt} is distributed normally with variance σ_ϵ, we obtain an ordered probit for observed performance y_{jt} with

$$y_{jt} = \begin{cases} \text{increased} & \text{if} \quad \beta X_{it} > \alpha_{1jt} \\ \text{stayed the same} & \text{if} \quad \alpha_{1jt} > \beta X_{it} > \alpha_{2jt} \\ \text{decreased} & \text{if} \quad \beta X_{it} < \alpha_{2jt} \end{cases} \tag{12}$$

where α_{1jt} and α_{2jt} are unobserved parameters related to the performance of the workplace in the previous year.

To be added: innovation.

4 Results

Results for the estimation of the production function are shown in Table 4.

We show marginal effects for each of the three states and the six performance measures for the ordered probit in Tables 5 and 6.

Results for the impact of training on innovation are shown in Table **??**.

Discussion forthcoming.

5 Conclusion

Forthcoming.

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.

Ackerberg, D., K. Caves, and G. Frazer (2003). Structural identification of production functions. Technical report, University of Arizono, UCLA and University of Toronto.

Almeida, R. and P. Carneiro (2006). The return to firm investment in human capital. Technical report. IZA Discussion Paper #1937.

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.

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. Technical report, NBER Productivity Program Meeting.

Bishop, J. H. (1997). What we know about employer-provided training: A review of the litterature. 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. and L. Lynch (2001). How to compete: The impact of workplace practices and information technology on productivity. *The Review of Economics and Statistics 83*(3), 434–445.

Blundell, R. and S. Bond (1999). GMM estimation with persistent panel data: An application to production functions. Technical Report 99/04, Institute for Fiscal Studies.

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

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.

Dostie, B. and M.-P. Pelletier (2007). Les rendements de la formation en entreprise. *Canadian Public Policy 33*(1), 21–40.

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.

Gorodnichenko, Y. (2006). Using firm optimization to evaluate and estimate returns to scale. Technical report, University of Michigan.

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

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

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

Turcotte, J. and L. W. Rennison (2004). Productivity and wages: Measuring the effect of human capital and technology use from linked employer-employee data. *International Productivity Monitor* (9), 25–36.

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

Table 1: Summary statistics - 1999

Variable	Mean	Std Dev.
ln(Value added)	12.434	1.503
ln(K)	12.895	1.226
ln(L)	1.737	1.168
Workforce control variables		
Proportion unionized	.046	.179
Changes in business processes		
Integration	.096	.294
Re-engineering	.129	.335
TQM	.085	.279
Changes in delegation		
Centralization	.062	.241
Decentralization	.024	.153
Delayering	.028	.165
Dealings with other firms		
Outsource	.075	.263
Collaboration	.058	.233
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 = 4950

Table 2: Summary statistics - Innovation

	YES (%)
Improved processes	23.47
Improved products	31.67
New processes	18.61
New products	26.63

Table 3: Summary statistics - Subjective performance

	Increased	Remained the same	Decreased
Unit production cost	42.66	49.63	7.71
Productivity	37.08	55.39	7.53
Sales growth	44.56	37.45	17.99
Product Quality	29.61	69.28	1.11
Customer Satisfaction	33.88	64.58	1.53
Profitability	34.59	64.58	1.53

Table 4: Coefficient estimates - production function

	OLS			FE			B&B		
prop - classroom	0.124		0.125	0.051**		0.050**	0.049		0.062
	(0.047)		(0.057)	(0.024)		(0.025)	(0.034)		(0.041)
prop - on-the-job		0.030	-0.002		0.010	0.004		-0.007	-0.007
		(0.013)	(0.026)		(0.016)	(0.017)		(0.004)	(0.004)
Controls for									
workplace practices	YES	YES	YES	YES	YES	YES	YES	YES	YES
industry	YES	YES	YES	YES	YES	YES	YES	YES	YES
year	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	30567	30567	30567	30567	30567	30567	22879	22879	22879
R-squared	0.59	0.59	0.59						
Number of workplaces	7310	7310	7310	7310	7310	7310	6684	6684	6684

Bootstrapped standard errors in parentheses
significant at 10%; ** significant at 5%; *** significant at 1%

Table 5: Marginal effect - ordered probit

	Unit production cost			Productivity			Sales growth		
	Incr.	Same	Decr.	Incr.	Same	Decr.	Incr.	Same	Decr.
prop - classroom	0.013	-0.008	-0.004	0.021	-0.014	-0.007	0.006	-0.002	-0.004
	(0.011)	(0.007)	(0.004)	(0.014)	(0.009)	(0.005)	(0.009)	(0.003)	(0.006)
prop - on-the-job	0.006	-0.004	-0.002	0.029***	-0.019***	-0.010***	0.021***	-0.007***	-0.013***
	(0.005)	(0.003)	(0.002)	(0.008)	(0.005)	(0.003)	(0.006)	(0.002)	(0.004)
Controls for									
workplace practices	YES	YES	YES	YES	YES	YES	YES	YES	YES
industry	YES	YES	YES	YES	YES	YES	YES	YES	YES
year	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations		30567			30567			30567	
Number of workplaces		7310			7310			7310	

Bootstrapped standard errors in parentheses
significant at 10%; ** significant at 5%; *** significant at 1%

Table 6: Marginal effect - ordered probit

	Product Quality			Customer Satisfaction			Profitability		
	Incr.	Same	Decr.	Incr.	Same	Decr.	Incr.	Same	Decr.
prop - classroom	0.033***	-0.031***	-0.002***	0.013**	-0.012**	-0.001**	0.007***	-0.002***	-0.006***
	(0.012)	(0.012)	(0.001)	(0.006)	(0.006)	(0.001)	(0.002)	(0.000)	(0.001)
prop - on-the-job	0.014**	-0.013**	-0.001**	0.036***	-0.033***	-0.003***	0.017***	-0.004***	-0.013***
	(0.006)	(0.005)	(0.000)	(0.002)	(0.002)	(0.000)	(0.004)	(0.001)	(0.003)
Controls for									
workplace practices	YES	YES	YES	YES	YES	YES	YES	YES	YES
industry	YES	YES	YES	YES	YES	YES	YES	YES	YES
year	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations		30567			30567			30567	
Number of workplaces		7310			7310			7310	

Bootstrapped standard errors in parentheses
significant at 10%; ** significant at 5%; *** significant at 1%

Table 7: Marginal effects - innovation probit

	Impv prc	Impv prd	New prc	New prd
prop - classroom	0.025***	0.054***	0.028***	0.046***
	(0.004)	(0.003)	(0.010)	(0.014)
prop - on-the-job	0.076***	0.060***	0.051***	0.053***
	(0.007)	(0.009)	(0.003)	(0.008)
Controls for				
workplace practices	YES	YES	YES	YES
industry	YES	YES	YES	YES
year	YES	YES	YES	YES
Observations	30567			
Number of workplaces	7310			

Bootstrapped standard errors in parentheses
significant at 10%; ** significant at 5%; *** significant at 1%