Skills Research Initiative
Initiative de recherche sur les compétences

The Determinants of Training Opportunities: Effects of Human Capital and Firm Characteristics

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Abstract

In this paper, we examine the determinants of training opportunities and the correlation between the incidence of various training activities (on-the-job and off-the-job) and accumulated schooling. We use two different data sources for the empirical analysis: the NLSY and the WES. Using the longitudinal information in NLSY, we assess the causality between training and education within a life cycle context. Using the rich information on both workers and workplaces in WES, we investigate the determinants training opportunities in Canada. The results indicate that there is a weak positive causal effect of schooling on training (on-the-job) after conditioning on unobserved abilities and tastes, and a weak negative correlation between unobserved abilities/tastes explaining schooling and on-the-job training. These results are consistent with the facts that more educated workers have lower costs of learning new skills and/or that schooling enhances the return to training. Our results from the WES data indicate that the incidence of training is stronger in skill intensive industries (or occupations) and positively correlated with workplace performance and technology use. Further, we found a positive correlation between training and education in the WES data as well.

Résumé

Dans cette étude, les auteurs examinent les déterminants des occasions de formation et la corrélation entre l'incidence de diverses activités de formation (sur les lieux ou à l'extérieur des lieux de travail) et la scolarité accumulée. Ils ont utilisé deux sources de données pour leur analyse empirique : l'Enquête longitudinale nationale sur les enfants et les jeunes (ELNEJ) et l'Enquête sur le lieu de travail et les employés (ELTE). À l'aide des données de l'ELNEJ, ils ont analysé la causalité entre la formation et les études dans le cadre du cycle d'une vie. À l'aide des précieux renseignements de l'ELTE sur les travailleurs et les milieux de travail, les auteurs ont examiné les déterminants des occasions de formation au Canada. Les résultats montrent, d'une part, un effet causal positif faible des études sur la formation (en milieu de travail) après avoir conditionné sur les habiletés et les goûts non observés et, d'autre part, une corrélation négative faible entre les habiletés et les goûts non observés à l'origine de la scolarité et la formation en milieu de travail. Ces résultats confirment le fait que l'acquisition de nouvelles compétences par les travailleurs scolarisés coûte moins cher et que la scolarité améliore le rendement de la formation. Les résultats obtenus par les auteurs à partir de l'ELTE montrent que l'incidence de la formation est plus forte dans les industries (ou les emplois) à coefficient élevé de compétences et qu'il y a une corrélation positive entre celle-ci et la performance en milieu de travail et l'utilisation de la technologie. De plus, les auteurs ont aussi constaté une corrélation positive entre la formation et les études dans l'ELTE.

1 Introduction

The human capital theory (Becker, 1964, and Mincer, 1974) provides a foundation for the study of the effects of training on labor market outcomes. For instance, the positive effect of training on labor market productivity is a central prediction of human capital theory. While various behavioral models have been advanced to explain the prevalence of upward wage profiles, human capital theory remains the most popular. In a standard Mincerian framework, individuals sacrifice present consumption in order to accumulate "skill units". These units, although intrinsically unobservable, are assumed to be correlated with schooling and post-schooling experience, through a production function. These assumptions have lead to the popular Mincerian wage regression, in which the effects of education and accumulated experience is separable. Another prediction of the classical human capital theory is that general training should be entirely financed by workers. General training produces skills that the worker can use with any employer, whereas specific training is only useful with the current employer. In competitive labor markets, firms have no incentive to pay for investments in general skills since the workers will capture all of the returns to such training.

However, these predictions are rarely verified in actual data. For example, economists have observed that the age earnings profiles of those who are more educated tend to be steeper than those of low educated people (Mincer, 1974). This is often explained by the conjunction of the existence of post-schooling training opportunities and heterogeneity in abilities and costs. The argument may be justified if, for example, tastes for schooling/academic abilities are negatively correlated with the innate cost of receiving training. If so, those who invest in schooling are also more likely to invest in on-the-job training. An alternative explanation for this correlation may be that accumulated schooling increases the incidence of training opportunities, even after conditioning on innate abilities. This may be justified if the marginal cost of training is decreasing with schooling (after conditioning on innate abilities) or if education magnifies the increase in productivity (the return to training). In a context where actual post-schooling human capital investments are proxied by measured experience, this suggests that log wages regression may not be separable in education and experience and, in particular, that the return to experience may be affected by schooling. While a positive correlation between education and training is plausible, it is not the only possibility. In practice, training decisions are jointly decided by workers and firms. In an environment where resources devoted to training are scarce, firms may prefer to train the low educated if the marginal benefit of training the low educated is higher than the highly educated workers. Under such a scenario, training may be viewed as a substitute for schooling. The sign of the correlation between education and training is therefore ambiguous.

In the empirical literature on training, it is customary to report a positive correlation between training and education as well as a certain degree of persistence in the individual incidence of training (see e.g. Lynch, 1992 and Altonji and Spletzer, 1991). However, one should be reluctant to give a structural interpretation to the correlation between training and education and between training and past training incidence. As indicated above, the measured correlation may be explained by the fact that preferences, prices or other constraints affecting future training decisions are directly affected by the occurrence of training and/or education as well as by unobserved differences, correlated over time and improperly treated, which create a spurious correlation between future and past experience (Heckman, 1981). Indeed, the distinction between true and spurious state dependence is central to several empirical issues related to the labor market. As of now, a thorough review of the literature reveals that it is impossible to establish whether the correlation between training and schooling is causal or spurious.

Regarding who pays for training, previous studies have reported that firms often finance training of workers even if that training is general in its nature (e.g. Loewenstein and Spletzer, 1998). The apprenticeship system in Germany is just one example of firms voluntarily providing their workers with general skills. However, just because a firm offers general training to its workers it does not necessarily imply that they pay the entire cost since the workers may accept a wage below their marginal product during the training period. However, it appears that employers generally pay for at least part of the training costs. This contradiction to the classical theory has recently inspired developments of new theoretical models (e.g. Acemoglu and Pischke, 1999a and 1999b) emphasizing the importance of labor market frictions - such as search costs, information asymmetries, unions, and minimum wage laws - which will distort the wage structure away from that prevailing in a competitive labor market. In presence of such frictions, investments in training will bet set to a level which is below the social optimum that is achieved in the classical human capital model, and Acemoglu and Pischke, 1999a, reports that more frictional and regulated labor markets may encourage more firm-sponsored training. This result is supported by the observation that firms appear to contribute more towards general training in Europe and Japan than in North America, combined with the fact that they have more regulated and frictional labor markets than Canada and the U.S. The results also imply that the positive wage returns that have been reported in the previous literature (e.g. Lynch, 1992) may underestimate the true return if employers are paying a portion of the costs associated with such training.

One of the main objectives with this paper is to estimate a dynamic model of education and training choices over a finite horizon using data extracted from the National Longitudinal Survey of Youth (NLSY). In our model, the intertemporal utility of choosing a particular option is a function of initial individual endowments, which has an observable component (proxied by parents background variables and Armed Force Qualification Test scores) as well as an unobserved component, and also depends on accumulated human capital (accumulated years of schooling, accumulated years of on-the-job training and accumulated years of off-the-job training). The dependence of the utility of choosing training on accumulated human capital (say schooling or past training) may be explained by the fact that accumulated human capital reduce the marginal costs of training or that, other things equal, employers who offer training opportunities tend to favor those who have accumulated more human capital (conditional on tastes and abilities). The model is therefore able to quantify the portion of the correlation between training and education that is explained by sorting (correlated tastes and abilities) and the portion of the correlation that is due to explained by structural dependence. It is also able to offer a similar decomposition of the persistence in life-cycle training decisions.

Another objective with this paper is to estimate the effects of both worker attributes and workplace characteristics on training participation in Canada using data extracted from the Workplace and Employee Survey (WES). While WES is less suited for assessing the causal effects of accumulated human capital on the incidence of training within the dynamic model presented below, it is well suited for estimating effects of workplace characteristics (such as number of employees, industry, composition of workforce etc.) and individual attributes on the probability of receiving training. Such characteristics are generally not observed in standard household surveys. However, even if there is a longitudinal element to WES, primarily at the workplace level, the short time length of the panel at the worker level (two years) does not allow us to estimate a dynamic model of education and training decisions. The results on the effects of worker characteristics must therefore be interpreted with some care, and not be thought of as necessarily describing any causal relationships.

From our analysis carried out using the NLSY, and to the extent that the US and Canadian labor markets do not differ substantially, we conclude that there is a small but positive correlation between education and post-schooling training. One possible explanation for this result is that more educated workers have lower costs of learning new skills. Another possibility is that schooling enhances the return to training. This may be true regardless of who pays for training. Along with the relatively low return to on-the job training found in the recent literature, this indicates that policies targeted to skill formation cannot solely be restricted to on-the-job training. Education is important as it enhances worker flexibility and, in particular, favors the incidence of training in the future. Our results obtained with the WES data set are not as easily translated in policy recommendations. However, we observe a positive correlation between training and education in the WES data as well. Further, the incidence of training is stronger in skill intensive industries (or occupations) and positively correlated with workplace performance and technology use.

The reminder of the paper is structured as follows. The data sources and sample selections are presented in Section 2 while the dynamic model of education and training choices is presented in Section 3. In Section 4, we discuss the empirical strategy used to estimate the parameters of the dynamic model. The main results on the effects of human capital on training are discussed in Section 5 while results generated from WES will be presented and discussed in Section 6. Finally, Section 7 concludes the paper.

2 The Data

2.1 NLSY

We use the 1979 cohort of the NLSY. In line with most previous research based on NLSY, we focus on a sample of white males. This allows us to avoid modeling fertility and occupation over the life cycle. As is well known, the NLSY has relatively comprehensive information on education, employment, wages and training. The NLSY is therefore most appropriate for analyzing the causal link between education and training. Respondents are asked about what types of training they had received and the different types of training are separated in three categories: company training (on-the-job training), apprenticeships and training obtained outside the firm (off-the-job training). The off-the-job training category includes business courses, barber and beauty schools, vocational institutes, nursing programs and correspondence courses. Despite its name, the incidence of off-the-job training does not require current employment. Our definitions are quite standard, for instance they are the same as those used in Lynch, 1991. In as much as it is natural to associate on-the-job training to firm specific training and off-the-job training to general training, the distinction between general and specific training does not play a central role in our analysis as we are not modeling job mobility.

While the information regarding the type of training is detailed, the measure of training intensity is far from being perfect. Before 1988, the NLSY specifies both starting and ending dates of all training spells that lasted at least one month. After 1988, all spells are reported and very short spells of training are therefore likely to be under-reported before 1988. Furthermore, as the NLSY does not report actual hours of training per week, it is not possible to measure actual training duration (or intensity) in a meaningful fashion. For this reason, we decided to focus on the incidence of training.

The sample data analyzed in this paper were obtained as follows:

- As we need to observe the full realization of the incidence of training for every individual, we need to focus on individuals who, most likely, could not have received training before 1979. For this reason, we selected white males aged between 14 and 16 years old in 1979. This is a sample very close to the sample analyzed by Eckstein and Wolpin, 1999.

- As a second step, we kept the individuals for whom we had non-missing information on the most important measured characteristics (parents' education, income, number of siblings, presence of both parents at age 14, rural/urban indicator, and Armed Forces Qualification Test (AFQT) scores). These characteristics are standard in the literature and they are the same as those used in various studies, such as Cameron and Heckman, 1998 and 2001, and Belzil and Hansen, 2002 and 2003. After these selections, we obtained a sample of 667 individuals.

- In order to control for the fact that individuals might have taken the AFQT at different ages and different schooling levels, we use a corrected measure. This corrected measure is based on the residuals from an OLS regression of AFQT scores on age and education. This is common in the literature (see for instance Cameron and Heckman, 1998).

- It is well known that training is very difficult to quantify and measure (see Barron, Berger, and Black, 1997). As a consequence, we focus only on the incidence of training and measure training in years. Thus, the return to training is subsumed in the return to experience for a year during which training has occurred.

- For symmetry, work experience (just like education) is also reported in years. At the estimation level, this allows us to compare the return to a year of schooling and experience with the return to experience over a year during which job training occurred.

- The individual histories are described as a sequence of mutually exclusive states. These states correspond to potential combinations of the potential fundamental choices taken by the individuals in our sample. These fundamental choices include schooling, home production, work, off-the-job training, apprenticeship and on-the-job training. Given the size of the sample and the very large number of combinations, we decided to group Apprenticeship with on-the-job training. We also chose not to distinguish between schooling and off-the-job training since both activities are closely related to the notion of "general" training.[1] As we also found a very small number of individuals who report both on-the-job and off-the job training (only 3), we decided to disregard these individuals. To reduce the number of states, we also decided to group those who work while in school with those who are in school without working into a single group. As a result, we obtain five potential states:[2] (1) School and/or Off-the-job training, (2) Work (no training), (3) Work/on-the job training, (4) Work/off-the job training, and (5) Home.

- The data used in this study cover the 1979-1994 period. While data are available for a few years posterior to 1994, the sampling procedure becomes biannual in the mid-nineties. For this reason, we do not use any data beyond 1994.[3]

The main features of the data may be found upon looking at Tables 1-3. Overall, training is relatively common, especially around the age of 25-26. At age 26, around 22% of the young individuals report having received some training during that year and on-the-job training appears the dominant form of training (13% having received on-the-job training and 9% having received off-the-job training). Before 20, off-the-job training is the dominant form of training. After 20, it is on-the-job training which becomes more common. This is essentially explained by the work patterns of young individuals; namely that the majority of young individuals is still in school at age 18.

As reported in the literature (Lynch, 1992, and Altonji and Spletzer, 1991), we also find that the incidence of training is positively correlated with schooling and that there is a certain degree of persistence in training. This may be verified upon looking at the results obtained from simple OLS regressions of the propensity to obtain on-the-job training and off-the-job training in a given year on some measures of accumulated human capital. These are found in Tables 4A and 4B. The dependent variable is equal to 1 if the young individual has received on-the-job training (OJT) during his last year observed in the sample and 0 if not. Accumulated education, accumulated on-the-job training (OJT), accumulated off-the-job training (OFT) and accumulated experience are measured at the beginning of the last year of observation and reflect all

[1] The classical distinction between general and specific training has been strongly questioned in recent years. For more discussions, see Acemoglu and Pischke, 1999a and 1999b.

[2] It should be noted that the number of combinations is limited by the fact that some actions are mutually exclusive by construction (school and home production).

[3] This is also the case in most recent research based on the NLSY.

past human capital decisions from the age of 14 until the second last year of observation.

Regarding the determinants of on-the-job training (Table 4A), the results indicate that, while there is a positive correlation between schooling and on-the-job training, the positive correlation between receiving training and the amount of training accumulated in the past is much stronger. When accumulated on-the-job training is controlled for, the effect of accumulated schooling drops from 0.011 to 0.008 and its level of significance also drops substantially. On the other hand, accumulated on-the-job training has a positive effect on the incidence of training and this effect remains quite robust (around 0.04) whether or not schooling is accounted for or not. The correlation between the incidence of on-the-job training and accumulated off-the-job training is weak when accumulated on-the-job training is controlled for.

The main difference between the incidence of on-the-job training and off-the-job training (Table 4B), is the significant positive effect that accumulated education has on off-the-job training. Accumulated off-the-job training is also strongly and positively correlated with the incidence of off-the-job training but the effect of accumulated on-the-job training appears insignificant.

To summarize, our data indicate that the positive correlation between education and training is much stronger for off-the-job training than on-the job training, and that there is a high degree of persistence in both types of training. These are the features of the data that we will try to explain with our structural model.

2.2 WES

To assess the effects of worker and firm characteristics on training participation in Canada, we will rely on information from the Workplace and Employee Survey (WES), which provides longitudinal information on both workers and firms. The unit of analysis will be the individual worker, and the outcome variable of primary interest will be an indicator for participation in training during the current year. In WES, workers are observed for two consecutive years while firms are observed for a minimum of 5 years. The short time length of the panel at the worker level does not allow us to estimate a dynamic model of education and training decisions, such as the one that will be implemented on the NLSY data, but does allow us to describe the relationship between worker and workplace characteristics and the incidence of training.

In WES, the target population for the employer is defined as all business locations in Canada that have paid employees.[4] The employee target population consists of those individuals who work for the target employers and who receive a Customs Canada and Revenue Agency T-4 Supplementary form. The survey is longitudinal of an annual frequency and was effective as of 1999. The employer component was stratified by three groups; industry, region and size. The WES survey collected data from 6,351 employers. Interviews were conducted on those employees who worked for the selected workplaces. A maximum of 12 employee interviews per target employer was set and for those workplaces where there were fewer than 4 employees, all were interviewed. There were two questionnaires created for the survey. The employer questionnaire introduces a means to measure such concepts as workforce characteristics and job organization, compensation, training, human resource function, collective bargaining, establishment performance, business strategy, innovation, technology use, and use of government programs. The questionnaire for the employee covered job characteristics requirements when hired, hours of work, pay and benefits, work stoppages, recent work history, education, family situation, and membership in designated employee equity groups.

In this paper, we will use the most recent data which refers to the calendar year 2001. After removing workers with missing information on relevant variables, we are left with a sample of 19,222 workers. To ensure that our results are representative for the population, the weights provided by Statistics Canada will be used in all subsequent analysis using WES.

The training information in WES is quite detailed. For instance, we have information on whether a worker received any training in the past 12 months that was not paid by the employer. We also know if the worker received any training that was paid during the same time period. The nature of training is also known, and we can distinguish between on-the-job training (training related to the job) and "career-oriented" training that is not directly related to the job. The latter corresponds in nature to off-the-job training discussed above. In the paper, we will consider four different outcome variables: i) an indicator for any training during the last 12 months, ii) an indicator for any training paid by the employer during the last 12 months, iii) an indicator for any on-the-job training during the last 12 months, and finally, iv) an indicator

[4] There are two exceptions to this: i) employers in Yukon and the Northwest Territories, and ii) employers who operate within the fields of crop and animal production; fishing, hunting and trapping; private households and public administration.

for any off-the-job training during the last 12 months.

The information on workers is similar to that found in most household surveys. For example, we have information on age, gender, education, wage, occupation, children, immigrant status, and union status. The workplace characteristics considered in this paper include number of employees, fraction of employees working full-time, technology use (captured by fraction of employees using computers and other technologies), establishment performance (captured by changes in workforce, gross payroll, and an indicator for changes in profits), and industry code.

Descriptive statistics on employee characteristics, using the sample weights provided in WES, are provided in Table 5A. The entries in the table indicate that 56.3% of employees received some training during the 12-month period preceding the interview. This fraction refers to any type of training, general or specific and paid or unpaid, and is higher than the proportion found for the NLSY data. There are at least two reasons for the higher incidence of training in WES compared to the NLSY. First, the NLSY sample consists of younger respondents, some of whom are still enrolled in school and have not yet obtained strong attachments to the labor market. Second, the last survey year of NLSY data used in this paper is 1994, whereas WES refers to activities during 2000 and 2001. It is likely that training has become more common during the second half of the 1990s and the higher fractions of respondents with any training in WES may, in part, reflect differences in timing of the data. Table 5A also reveals that most training of workers were either paid or subsidized by the employers. The proportion that received any paid training during the past 12 months is 33.3%. The fraction of workers that received on-the-job training is 31.6% while the proportion that received any paid off-the-job training (defined as career-oriented training that is not directly related to the job) during the last 12 months is 3.8%. Thus, consistent with economic theory but contradicting the findings in Loewenstein and Spletzer, 1998, firms are less willing to invest in general skills of their workers and instead promote training related to the job. Regarding other observable characteristics of employees, 15.9% have not completed high school while 76.8% report a high school diploma as their highest educational attainment. Most workers in the data work full-time (defined as 30 hours or more per week) and 24.9% are members of a union or covered by a collective bargaining agreement. The WES survey also provides information on occupations aggregated into six categories: (i) managers, (ii) professionals, (iii) technical/trades, (iv) marketing/sales, (v) clerical/administrative, and (vi) production, operation and maintenance. Most workers belong to the technical/trades category (43%) while the categories marketing/sales and production, operation and maintenance contain the fewest workers (around 7-8%). Finally, almost 60% use computers at work and 13.5% use other forms of technology at work.

Information on workplace characteristics is provided in Table 5B. The entries in the table, again weighted by the sample weights provided in WES, are based on 5,183 workplaces. Most workplaces employ less than 100 workers (32.5% employ 1-19 workers while 31.7% employ 20-99 workers) while the proportion of large workplaces (employing 500 workers or more) is 15.4%. The fraction of full-time employees is 74.4% and the average gross payroll per employee is \$33,400. About 18% of workplaces belong to non-profit organizations. WES also includes some information on workplace performance and we have included measures on changes in profits and work force in the analysis. As can be seen in Table 5B, almost 40% of the workplaces reported an increase in profits between 2000 and 2001, while 20% reported a decrease in profits over the same period. Finally, about 31% reported a decrease in the number of employees between 2000 and 2001.

3 A dynamic model of education and training

We will assume that individuals maximize expected lifetime utility by choosing the optimal state over a finite horizon T. Lifetime utility is time additive and there are K mutually exclusive states. The objective function is therefore

$$Max_{\{d_{kt}\}}\ E(\sum_{t=0}^{T}\beta^t\cdot(\sum_{k=1}^{K}U_{kt}\cdot d_{kt})\mid\Omega_t) \tag{1}$$

where the control variables, d_{kt}, are equal to one when option k is chosen and 0 if not, U_{kt} denotes the contemporaneous (per-period) utility of choosing option k at age t, and β is the yearly discount factor. The information set, at date t, is denoted Ω_t.

The maximum expected value achieved at date t, denoted $V(\Omega_t)$, is given as follows

$$Max_{\{d_{kt}\}}E(\sum_{t=0}^{T}\beta^t\cdot(\sum_{k=1}^{K}U_{kt}\cdot d_{kt})\mid\Omega_t)=Max_{k\in K}V_k(\Omega_t)=V(\Omega_t) \tag{2}$$

where the alternative specific value functions, $V_{kt}(\Omega_t)$, are given by the following expression,

$$V_{kt}(\Omega_t) = U_{kt} + \beta EV_{t+1}(\Omega_{t+1} \mid d_{kt} = 1) \tag{3}$$

and where $EV_{t+1}(\Omega_{t+1} \mid d_{kt} = 1)$ denotes the value of following the optimal policy in period t+1 .

We follow an approach similar to Cameron and Heckman, 2001, and approximate the alternative specific value functions,$V_{kt}(.)$, using a flexible (quadratic) functional form. That is, the intertemporal utility of choosing a given state k at age t is assumed to be of the following form

$$\begin{aligned} V_{kt} &= X'\beta_{kt} + \psi_{kt}(S_t) + \varphi_{1kt}(EX_t) \\ &\quad + \varphi_{2kt}(OJT_t) + \varphi_{3kt}(OFT_t) + \varphi_{4kt} \cdot H_t + \eta_k + \varepsilon_{kt} \end{aligned} \tag{4}$$

for $k = 1, 2...K$ and where the dependence of all the regression parameters $(\beta_{kt}, \varphi_{1kt}, \varphi_{2kt}, \varphi_{1kt})$ and the function (ψ_{kt}) on k and t allows for a maximum degree of flexibility at the estimation level. The variables and parameters are defined as follows,

- S_t is accumulated schooling at age t.
- EX_t is accumulated years of experience at age t.
- OJT_t is accumulated years in which on-the-Job Training took place.
- OFT_t is accumulated years in which off-the-Job Training took place.
- H_t is accumulated years of home time.
- The vector X contains household human capital variables which act as proxies for the initial ability/taste endowments. These include mother's education, father's education, family income (as measured in thousands of 1978 dollars), number of siblings, an indicator equal to 1 (Nuclear) for the presence of both biological parents at age 14 (and 0 if not) and Armed Forces Qualification Test (AFQT) scores.
- The function ψ_{kt} captures the structural effect of accumulated schooling on the utility of choosing state k (including training).

- The functions $\varphi_{1k}(.), \varphi_{2k}(.)$ and $\varphi_{3k}(.)$ capture the structural effects of accumulated experience, accumulated on-the-job training and accumulated off-the-job training on the utility of choosing state k.

- The term η_k represents a state specific unobserved heterogeneity term representing individual differences in tastes for all relevant combinations of schooling, work, home production and training.

4 Estimation Strategy

In order to estimate the model, some restrictions need to be imposed. These restrictions will reflect the necessity to keep the number of parameters at a manageable level as well as the necessity to hold the model to a certain level of coherency.

- To reduced the number of parameters, we assume that the vector of parameters β_{kt} remains constant over some age intervals. We actually experimented with 2 possibilities. In a first case, the intervals chosen are 14-19, 20-25 and 26 or more. The second option considered is to have 2 intervals; 14 to 21 and 22 to 30.

- Because most individuals are in school in the early phase of the life-cycle, it is practically impossible to allow the effects of parents background to vary with age. For this reason, the effects of parents background are assumed to be constant for the School option. For a similar reason, it is also practically impossible to allow the utility of attending school to depend on accumulated experience and training. The corresponding parameters are therefore set to 0.

- The function $\psi_{kt}(.)$ is estimated flexibly so to mimic a non-parametric regression. With respect to the utility of school (as well as school/off-the-job training), the $\psi_{kt}(.)$ function is estimated using a specific intercept term for each potential grade level. As most people reach their maximum schooling attainment without any interruption, we do not allow for age/grade specific effects. For other choices (training and work), the $\psi_{kt}(.)$ is specified as a spline function with 4 segments; high school dropouts ($S_t < 12$), high school graduates ($S_t = 12$), some college ($12 < S_t < 16$) and college graduate ($S_t > 16$).

- The functions $\varphi_{1k}(.), \varphi_{2k}(.)$ and $\varphi_{3k}(.)$ are assumed to be quadratic.
- We assume that

$$\eta_k = \alpha_{0k} + \alpha_{1k} * \mu \tag{5}$$

where the distribution of μ is approximated by a discrete distribution with two points of support point (μ_1 and μ_2). The type probabilities are estimated using logistic transforms (i.e. the probability of type 1 is estimated as $exp(q)/(1 + exp(q))$). In order to obtain identification, we normalize μ_1 to 0 and α_{11} to 1 (the unobserved taste for schooling).

- The term ε_{kt} represents a pure stochastic i.i.d. shock observed (by the agent) at the beginning of period t. We assume that the cumulative distribution of the $\varepsilon_{kt}'s$ is an Extreme Value of type 1 (i.e.: Prob $(\varepsilon < e) = F(e) = \exp(-\exp(-e)))$.
- The final date, T, is set at age 31.

The distributional assumption, coupled with the model structure already laid out, will imply that,

$$\Pr(d_{kt} = 1) = \frac{\exp(\bar{V}_{kt})}{\sum_{j=1}^{K} \exp(\bar{V}_{jt})} \tag{6}$$

where

$$\bar{V}_{kt} = V_{kt} - \varepsilon_{kt} \tag{7}$$

The model is estimated by maximum likelihood techniques. Altogether, the implementation of the model requires estimation of 197 parameters. The type specific likelihood function, $L(.|\mu)$ is given by

$$L(.|\mu) = \Pi_{t=1}^{T} \Pr(d_{kt} = 1 \mid \mu)$$

and the unconditional likelihood function is just a weighted average of $L(.|\mu)$, that is

$$L(.) = \sum_{i=1}^{I} L(. \mid \mu_i) \cdot p_i \tag{8}$$

5 Results from a dynamic model of education and training

This section is divided into four subsections. In Section 5.1, the capacity of the model to generate predictions that closely resembles the observed patterns is discussed. The causal effect of accumulated human capital on training is discussed in Section 5.2, while Section 5.3 discusses the effects of parental background variables. Finally, the population distribution of unobserved initial taste and ability endowments are discussed in Section 5.4.

The discussion will focus on two main choices; work/on-the-job training and work/off-the-job training. These are the two main options which characterize post-schooling investment decisions taken by the young individuals sampled in the NLSY.

5.1 Predicted frequencies and goodness of fit

Despite the relatively high degree of asymmetry in the actual frequencies between all the possible options (some options are only rarely chosen), our predicted frequencies (found in Table 6) indicate that our model is able to fit the data quite well. In particular, we capture the increase in the incidence of on-the-job training from age 22 to age 26 (the peak age for on-the-job training). The incidence of off-the-job training/work and household activities (home) are also predicted quite accurately. Finally, we note that our model predicts a high proportion of young individuals in school until age 17 and then a rapid decline in school attendance, although it seems to over-predict slightly school attendance beyond age 23.

5.2 The causal effect of human capital on training

The estimates of the causal effects of accumulated schooling on the intertemporal utility of choosing various options are found in Table 7. Overall, the utility of working with or without training is increasing in accumulated schooling. However, the effect is small and insignificant for the working/on-the job training option. Given the complexity of the model and the inherent normalizations required in a logistic model, the parameter estimates raise less interest than their corresponding marginal effects on the incidence of choosing various options. To illustrate the causal impact of accumulated schooling on training, the parameter estimates have been transformed into marginal effects. These are found in Table 8. They have been computed at age 26 (when practically everyone is out of school) and are evaluated at average values of the observable characteristics. Overall, the marginal effects indicate that accumulated schooling has only a negligible effect on both types of training. The average marginal effect for on the-job training, 0.0014, is small and indicates that on average, those with more schooling are slightly more likely to obtain on-the-job training. Our estimate of the effect of schooling on off-the-job training is also positive and close to zero (0.0013). While the marginal effect of schooling is small for options that include some element of training, it is quite large and positive for the work with no training option (0.07).

Regarding accumulated work experience, the entries in Table 8 suggest small effects of this on the incidence of training. The marginal effects are 0.01 for work/on-the-job training and 0.0015 for work/off-the-job training. As with accumulated education, the largest effect is found for the work with no training option (0.11).

While accumulated education and experience have only small positive effects on the incidence of training, we find that the marginal effect of an additional year of training (in the past) is more important. For instance, the marginal effect of one year of on-the-job training is positive and quite large (0.02) on the probability of obtaining on-the-job training but negative on the probability of working with no training (-0.044). For obtaining off-the-job training, the effect is very small (0.0006). Accumulated off-the-job training increases the incidence of both types of training as well as the probability of working with no training.

Finally, we find strong evidence that accumulated home time will reduce both the incidence of on-the-job training and off-the job training, although the effect for on-the-job training is much stronger. Both the structural utility parameters and their marginal effects are negative. This is consistent with the fact that accumulated home time might depreciate market skills and reduces access to employment.

5.3 The effects of household human capital on schooling and training opportunities

It is well recognized that parents' background variables, such as parents' education and income, are strongly correlated with school attendance (Cameron and Heckman, 1998, and Belzil and Hansen, 2002). This positive correlation is consistent with the view that those raised in wealthier families will enjoy better education financing as well as the view that the intergenerational education correlation is explained by abilities transferred across generation. The effects of parents' background variables on wages appear much weaker (e.g. Belzil and Hansen, 2003). From the estimates reported in Table 9, it is possible to infer the relative importance of these background variables on the utility of choosing training as opposed to the utility of being in school.

The structural estimates found in the first row (for the schooling option) indicate that the utility of being in school increases with father's and mother's education, family income, and is negatively related to the number of siblings. All of these corresponding parameters are highly significant. However, as with the effects of accumulated human capital, the estimates are difficult to interpret within the complex model, and we therefore present the marginal effects of parent's education and income in the lower part of Table 8. In order to quantify the absolute probabilities, it is informative to relate the marginal effects to the absolute (predicted) probabilities of Table 6. These marginal effects suggest that the incidence of training increases in parent's education while it is unrelated to their income. The effect of parent's education is strong for on-the-job training than for off-the-job training and this is also consistent with the estimates shown in Table 9. This is consistent with the hypothesis that training incidence is related to individual skill endowments and, furthermore, that individual skill endowments are partly explained by patents' background variables.

5.4 Unobserved tastes/abilities for schooling and training

The parameters that characterize the distribution of unobserved heterogeneity are found in Table 10. As we included an intercept term for each option, the first point of support of both factors is normalized to 0. The loading factors indicate that unobserved taste for on-the-job training is only weakly correlated with taste for schooling; the estimate is close to zero (-0.126) and is not significant at conventional levels. Taste for work/off-the job training also appear to be negatively correlated with taste for schooling, however, in this case the loading estimate is significantly different from zero. Altogether, these estimates suggest only a weak correlation between the incidence of on-the-job training and unobserved academic skills while off-the-job training and such unobserved skills appear negatively correlated.

6 Results from WES

The WES data was used to estimate linear probability models of training incidence where the standard errors are corrected for the clustering in the data. The clustering occurs because we regress training information at the individual level on individual and workplace characteristics, the latter represented by variables that only varies across workplaces. The estimation results are presented in Tables 11 and 12. The entries in the first two columns of Table 11 refer to a specification that uses any training as the outcome variable. In columns three and four, results using any paid training as the dependent variable are shown. In Table 12, the first two columns refer to a specification that regress on-the-job training on observable characteristics while the last two columns uses off-the-job training as the dependent variable instead.

Regarding any training, the entries in Table 11 suggest that older workers are less likely to receive training. This is consistent with standard human capital theory that suggests that training should decrease with age, both because of higher opportunity costs and also because there is less time left to reap of the benefits from training. While gender, presence of dependent children, and immigrant status has no significant effects on the incidence of training, there is a positive and significant effect of education. This positive partial correlation was found in the NLSY data (see Tables 4A and 4B) and has also been documented elsewhere. However, as discussed above, the WES results are based on reduced form regressions on a cross-section of workers and must therefore be interpreted with some care, and not be thought of as necessarily describing any causal relationships. There appears to be no significant differences in the incidence of training across occupations, with the exception of clerical/administrative occupations whose estimated coefficient is negative and significant suggesting that workers in these types of jobs receive less training than other workers. The results for any training also suggest that there is a positive relationship between technology use and training. The coefficients on computer use at work and use of other technologies are both positive and statistically significant at conventional levels implying a higher incidence of training in jobs where technologies are used. This result is expected as skills upgrading is likely to be more important in these types of jobs.

Regarding the effects of workplace characteristics, the entries in Table 11 suggest that there are some significant industry differences in training. The lowest incidence of training appears in the following industries: labor intensive tertiary manufacturing, primary product manufacturing, retail trade and consumer services, and real estate, rental and leasing operations. The highest incidence of training appears in communication and other utilities and in finance and insurance. These industry differences appear, to some extent, be driven by differences in the skill levels of the employees but remain after controls for education have been included. Moreover, there is a significant relationship between workplace size and training, where the incidence of training is significantly higher in workplaces with more that 19 employees. A possible reason for the positive link between workplace size and training is lower costs associated with provision of training in larger firms. This result may also partially explain the common finding in the literature that larger firms tend to pay higher wages. Generally, these studies have not controlled for provision of job training and some of the wage premium observed in the data may therefore be due to a higher incidence of training in large firms, assuming that training increases productivity and wages. The regression specifications used in this paper also incorporate information changes in profits and in the number of employees. The results suggest that workplaces that reported an increase in profit between 2000 and 2001 provided more training during 2001 than other firms/workplaces. Thus, firms appear to invest a portion of their profits in their labor force. Further, firms that downsized between 2000 and 2001 provided less training during 2001. Both these workplace characteristics are included to capture some of the effects of workplace performance on the provision of training, and they suggest that there is a significant relationship between performance and training.

The regression results in the first two columns of Table 11 refer to a specification that used any training as the dependent variable. The entries in columns 3 and 4 instead consider any form of training that is paid by the employer. Overall, the results are similar to those found for any training with a few exceptions. The coefficient associated with the immigrant indicator is negative and significant, suggesting that, everything observable held constant, immigrants receive less paid training than native born Canadians. The coefficient for any training was also negative, but smaller in absolute terms and not precisely estimated. This suggest that while there is no significant differences in participation in any type of training - paid or unpaid - between native born and immigrants, immigrants are less likely to receive paid training. As for any training, high school graduates appear to receive more training than high school drop-outs. However, there is no significant difference between high school drop-outs and workers who have obtained more than high school. Finally, the incidence of paid training is higher among workers who use computers or other technologies at work but only the former is statistically significant. Regarding workplace characteristics, the same pattern as for any training is observed. In particular, paid training is more common in larger workplaces and in workplaces that reported increased profits between 2000 and 2001.

The results in the first two columns of Table 12 indicate that age and presence of dependent children are negatively associated with the incidence of on-the-job training. It is also found that education and technology use are positively related to on-the-job training. These effects are similar to those reported above, both in terms of magnitudes and significance. However, contrary to the results for any training, there no significant industry or workplace size differences in on-the-job training and while the coefficient associated with increased profits is positive it is not significant. The final set of results in Table 12 refers to the incidence of paid or subsidized off-the-job training (training not directly related to the job). While most of the coefficients are similar to those previously discussed, one exception is the effect of education. The estimates for the variables representing high school and more than high school are numerically small (close to zero) and not significant. A possible reason for this may be the similarity between off-the-job training and education. However, the proportion of workers that received paid or subsidized off-the-job training is small and this fact may also contribute to the result.

Overall, the results from the WES data suggest a positive relationship between training and the skill level of workers. Workers that use computers or other forms of technology receive more training than other workers and training is more pronounced in industries that typically use more skilled workers. This is not surprising as training is perhaps the most important tool for firms to maintain or upgrade the skill level of their work force. However, the positive relationship between training and education found in the data may not necessarily indicate a causal relationship. Instead, some or all of the partial correlation may be due to existence of unobservable (to the researcher) characteristics that determine both educational attainments and participation in job training.

7 Summary and conclusions

In this paper, we have examined the determinants of training opportunities and the correlation between the incidence of various training activities (on-the-job and off-the-job) and accumulated schooling. We have used two different data sources for the empirical analysis: the NLSY and the WES. The nature of the two data sources allows us to address different issues. Using the longitudinal information in NLSY, we are able to assess the causality between training and education within a life cycle context. Using the rich information on both workers and workplaces in WES, we can investigate the determinants training opportunities in Canada. However, the limited longitudinal nature of the WES data does not allow us to model education and training as joint outcomes in a dynamic framework, like we do using the NLSY, and we cannot conclude if the estimated relationships using WES are causal or not. In fact, it is clear that efforts devoted to the development of Canadian panel data similar to those found in the NLSY for the US would be beneficial for future research in training opportunities. Only life cycle data will allow Canadian researchers to comprehend the key aspects of training and skill formation policies.

Our findings indicate that there is a weak positive correlation between schooling and post schooling training. Moreover, this correlation is decomposed into a weak positive causal effect of schooling on training (on-the-job) after conditioning on unobserved abilities and tastes, and a weak negative correlation between unobserved abilities/tastes explaining schooling and on-the-job training. One possible explanation is that more educated workers have lower costs of learning new skills. Another possibility is that schooling enhances the return to training. This may be true regardless of who pays for training. Along with the relatively low return to on-the job training found in the recent literature, this indicates that policies targeted to skill formation cannot solely be restricted to on-the-job training. Education is important as it enhances worker flexibility and, in particular, it favors the incidence of training in the future. Our results obtained with the WES data set are not as easily translated in policy recommendations. As seen earlier, the incidence of training is stronger in skill intensive industries (or occupations) but the cross-sectional nature of the WES data does not allow us to conclude if the relationships are causal. However, we observe a positive correlation between training and education in the WES data as well. Further, the incidence of training is stronger in skill intensive industries (or occupations) and positively correlated with workplace performance and technology use.

At this stage, we would like to stress that our model, as it is currently designed, does not allow us to distinguish between the effects that education may have on the return to on-the-job training as opposed to the cost of training per se. The current paper attempts to estimate the determinants of training opportunities and no attention is paid to the wage effects of training. In order to do so, it would be important to model wages simultaneously with training and educational decisions. We view this as the most important extension of this current research.

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Table 1. Descriptive Statistics for the NLSY sample.

	Mean	St dev.	# of individuals
Family income (in $)	28877	15086	667
Father's education	12.5	3.2	667
Mother's education	12.1	2.3	667
Number of siblings	2.7	1.7	667
Proportion raised in urban areas	0.74	0.44	667
AFQT scores	49.4	26.8	667
Proportion raised in a nuclear family	0.82	0.39	667
Schooling completed (1994)	12.7	2.4	667
Number of years with OJT (1994)	1.0	1.5	667
Number of years with OFT (1994)	0.8	1.2	667
Number of times observed in panel	15.1	3.5	667

Note: Family income is an average of two values taken as of May 1978 and May 80 respectively.

Table 2. Empirical frequencies by age in the NLSY

Age	School only	Work only	Work & OJT	Work & OFT	Home
14	0.999	0.000	0.000	0.000	0.002
15	0.977	0.000	0.005	0.000	0.009
16	0.943	0.006	0.021	0.000	0.030
17	0.858	0.076	0.030	0.006	0.011
18	0.624	0.267	0.032	0.028	0.048
19	0.387	0.442	0.020	0.030	0.120
20	0.328	0.496	0.044	0.017	0.115
21	0.262	0.550	0.055	0.011	0.123
22	0.189	0.635	0.057	0.020	0.100
23	0.112	0.673	0.090	0.041	0.085
24	0.081	0.657	0.137	0.052	0.071
25	0.052	0.689	0.128	0.064	0.068
26	0.049	0.667	0.147	0.078	0.060
27	0.040	0.694	0.140	0.066	0.061
28	0.024	0.740	0.132	0.050	0.054
29	0.029	0.780	0.107	0.047	0.038
30	0.008	0.777	0.106	0.044	0.065

Table 3. The Incidence of Training

Empirical Frequencies

Age	**OJT**	**OFT**	**Total**
14	0.000	0.002	0.002
15	0.005	0.044	0.049
16	0.021	0.080	0.101
17	0.030	0.085	0.115
18	0.032	0.084	0.116
19	0.020	0.059	0.079
20	0.044	0.027	0.071
21	0.055	0.015	0.070
22	0.057	0.024	0.081
23	0.090	0.055	0.145
24	0.137	0.067	0.204
25	0.128	0.073	0.201
26	0.147	0.091	0.238
27	0.140	0.076	0.216
28	0.132	0.054	0.186
29	0.107	0.055	0.162
30	0.106	0.044	0.150

Table 4A. OLS Regressions of the incidence of on-the-job training on accumulated human capital (T-ratios in parentheses)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Constant	-0.0639	0.0396	0.0626	0.0687	-0.0621	-0.0771	-0.0830
	(1.13)	(3.29)	(4.98)	(3.12)	(1.12)	(1.38)	(1.27)
Accumulated	0.0113	-	-	-	0.0082	0.0085	0.0087
Education	(2.57)				(1.89)	(1.97)	(1.94)
Accumulated	-	0.0461	-	-	0.0444	0.0426	0.0424
OJT		(6.22)			(5.96)	(5.67)	(5.60)
Accumulated	-		0.0223	-		0.0161	0.0158
OFT			(2.41)			(1.77)	(1.71)
Accumulated	-		-	0.0017	-	-	0.0005
experience				(0.56)			(0.18)

Note: The dependent variable is equal to 1 if the young individual has received on-the-job training (OJT) during his last year in the sample. Accumulated education, OJT, OFT, and Experience are measured at the beginning of the last year of observation and reflect all past human capital decisions from the age of 14 until the second last year of observation.

Table 4B. OLS Regressions of the incidence of off-the-job training on accumulated human capital (T-ratios in parentheses)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Constant	-0.0751	0.0323	0.0241	0.0319	-0.0882	-0.0884	-0.1037
	(1.97)	(3.87)	(2.85)	(2.15)	(2.29)	(2.29)	(2.30)
Accumulated	0.0087	-	-	-	0.0089	0.0089	0.0095
education	(2.92)				(2.99)	(2.99)	(3.05)
Accumulated	-	0.0025	-	-	-	-0.0009	-0.0014
OJT		(0.48)				(0.18)	(0.26)
Accumulated	-		0.0137	-	0.0142	0.0143	0.0137
OFT			(2.19)		(2.29)	(2.29)	(2.15)
Accumulated	-		-	0.0004	-	-	0.0014
experience				(0.20)			(0.65)

Note: The dependent variable is equal to 1 if the young individual has received off-the-job training (OFT) during his last year in the sample. Accumulated education, OJT, OFT, and Experience are measured at the beginning of the last year of observation and reflect all past human capital decisions from the age of 14 until the second last year of observation.

Table 5a. Employee Characteristics for the WES sample.

	Mean	St dev.
Any training during the past 12 months	0.563	0.496
Any training paid by employer during the past 12 months	0.333	0.471
Any on-the-job training during past 12 months	0.316	0.465
Any general training paid by employer during past 12 months	0.038	0.192
Age	39.3	11.1
Male	0.491	0.500
Presence of dependent children	0.468	0.499
Immigrant	0.197	0.398
High school	0.768	0.422
More than high school	0.073	0.261
Full-time employee	0.847	0.360
Covered by a CBA	0.249	0.432
Occupation: Managers	0.115	0.319
Occupation: Professionals	0.164	0.371
Occupation: Technical/Trades	0.430	0.495
Occupation: Marketing/Sales	0.080	0.271
Occupation: Clerical/Administrative	0.137	0.344
Occupation: Production workers	0.074	0.263
Using computer at work	0.596	0.491
Using other technology at work	0.135	0.342

Table 5b. Workplace Characteristics for the WES sample.

	Mean	St dev.
1-19 employees	0.325	0.468
20-99 employees	0.317	0.465
100-499 employees	0.205	0.403
500 employees or more	0.154	0.361
Fraction of workforce working full-time	0.744	0.285
Average gross payroll	33.4	21.3
Non-profit organization	0.182	0.386
Increase in profits between 2000 and 2001	0.397	0.489
Decrease in profits between 2000 and 2001	0.198	0.399
Decreased workforce between 2000 and 2001	0.311	0.463

Table 6. Goodness of fit: Predicted frequencies by age.

	Predicted Frequencies				
Age	**School only**	**Work only**	**Work & OJT**	**Work & OFT**	**Home**
14	**0.986**	**0.000**	**0.000**	**0.000**	**0.013**
15	**0.986**	**0.000**	**0.004**	**0.000**	**0.010**
16	**0.923**	**0.006**	**0.021**	**0.000**	**0.050**
17	**0.820**	**0.080**	**0.028**	**0.007**	**0.055**
18	**0.583**	**0.271**	**0.030**	**0.029**	**0.087**
19	**0.384**	**0.446**	**0.020**	**0.035**	**0.115**
20	**0.327**	**0.500**	**0.043**	**0.024**	**0.106**
21	**0.274**	**0.556**	**0.056**	**0.019**	**0.095**
22	**0.202**	**0.628**	**0.056**	**0.031**	**0.084**
23	**0.122**	**0.652**	**0.081**	**0.063**	**0.082**
24	**0.095**	**0.631**	**0.124**	**0.078**	**0.072**
25	**0.082**	**0.656**	**0.111**	**0.093**	**0.059**
26	**0.083**	**0.628**	**0.126**	**0.109**	**0.055**
27	**0.074**	**0.646**	**0.115**	**0.109**	**0.056**
28	**0.063**	**0.686**	**0.115**	**0.089**	**0.047**
29	**0.073**	**0.711**	**0.091**	**0.086**	**0.039**
30	**0.064**	**0.717**	**0.088**	**0.077**	**0.053**

Table 7. The causal effects of accumulated education on the intertemporal utility of choosing various options.

	Accumulated human capital				
	Education	**Experience**	**OJT**	**OFT**	**Home**
curent choices					
Work (no training)	0.3426	0.5374	-0.2114	1.27423	-1.4467
	(4.91)	(28.38)	(3.32)	(12.13)	(15.83)
Work/OJT	0.0369	0.2664	0.5733	0.9450	-1.1630
	(1.12)	(9.09)	(7.31)	(4.70)	6.55
Work/OFT	0.2770	0.3343	0.1294	3.7956	-4.0907
	(3.49)	(5.49)	(1.05)	(15.77)	(15.90)
School					-1.1949
					(19.05)

Note: Estimates obtained by maximizing the likelihood function in equation (8) in the text. t-ratios are presented in parentheses.

Table 8
Marginal effects of accumulated human capital on the incidence of on-the-job and off-the-job training

	Potential Choices					
Unobs. het.		**yes**			**no**	
AFQT scores		**no**			**yes**	
	work/ OJT	**work/ OFT**	**work/ no training**	**work/ OJT**	**work/ OFT**	**work/ no training**
acc. education	0.0014	0.0013	0.0714	-0.0002	0.0003	0.0276
acc. experience	0.0098	0.0015	0.1120	0.0106	0.0016	0.1550
acc. OJT	0.0211	0.0006	-0.0441	0.0181	0.0004	-0.0582
acc. OFT	0.0348	0.0176	0.2655	0.0293	0.0156	0.3169
acc. Home	-0.0428	-0.0189	-0.3015	-0.0368	-0.0152	-0.3773
Father's educ	0.0110	0.0009	-0.0051	0.0090	0.0007	-0.0017
Mother's educ	0.0135	0.0014	0.0005	0.0111	0.0010	0.0025
Family income	-0.0001	-0.0001	-0.0004	-0.0001	0.0000	0.0001

Table 9. The effects of family background

	Father's education	Mother's education	Fath.*Moth education	Family income	Number of siblings	Nuclear family
Choices						
Work	-0.0243	0.0025	-0.0014	-0.0003	0.0210	0.0081
	(0.58)	(0.06)	(0.45)	(0.07)	(0.81)	(0.10)
Work/OJT	0.3002	0.3675	-0.0242	-0.0028	-0.0732	0.1482
	(4.86)	(5.31)	(4.23)	(0.49)	1.84	(1.17)
Work/OFT	0.1934	0.2936	-0.0213	-0.0066	0.0295	-0.0116
	(1.62)	(3.16)	2.30	(0.83)	(0.56)	(0.10)
School	0.1569	0.1330	-0.0035	0.0078	-0.0954	0.3273
	(3.12)	(2.73)	(0.92)	(1.86)	(3.08)	(2.82)

Note: Estimates obtained by maximizing the likelihood function in equation (8) in the text. t-ratios are presented in parentheses.

Table 10. The Distribution of unobserved ability: Unobserved tastes for work and training

μ_2	1.9784
	(7.44)
q	-0.2987
	(1.99)
School/OFT	
α_{02}	0.0
	(fixed)
α_{12}	1.0
	(fixed)
Work	
α_{03}	-2.5892
	(4.38)
α_{13}	-0.6193
	(3.87)
Work/OJT	
α_{04}	-5.7676
	(7.92)
α_{14}	-0.1255
	(1.28)
work/OFT	
α_{05}	-7.3524
	(-4.51)
α_{05}	-0.5707
	(3.22)

Note: Estimates obtained by maximizing the likelihood function in equation (8) in the text. t-ratios are presented in parentheses. The estimate of q implies that 42.6% of the sample are estimated to be type 1 indivdiuals.

Table 11. Effects of worker and workplace characteristics on the incidence of any training and any paid training.

	Any training		Any paid training	
	Estimate	s.e.	Estimate	s.e.
Worker characteristics				
Age	-0.005	0.001	-0.001	0.001
Male	0.001	0.018	0.0001	0.017
Children	-0.016	0.015	0.002	0.013
Immigrant	-0.022	0.022	-0.036	0.019
High school	0.084	0.021	0.053	0.017
More than high school	0.126	0.034	0.038	0.030
Full-time employee	0.009	0.025	0.026	0.021
ocp2	0.028	0.030	0.050	0.031
ocp3	-0.013	0.031	0.016	0.025
ocp4	-0.064	0.052	-0.045	0.037
ocp5	-0.108	0.034	-0.100	0.026
ocp6	-0.034	0.044	-0.025	0.034
cba	0.004	0.019	-0.021	0.020
dcpu	0.156	0.021	0.109	0.020
dtech	0.076	0.022	0.040	0.023
Workplace characteristics				
ind2	-0.190	0.043	-0.197	0.044
ind3	-0.085	0.041	-0.128	0.044
ind4	-0.075	0.039	-0.133	0.043
ind5	-0.038	0.041	-0.108	0.042
ind6	-0.067	0.044	-0.077	0.044
ind7	-0.060	0.042	-0.060	0.045
ind8	0.113	0.043	0.173	0.047
ind9	-0.103	0.044	-0.142	0.046
ind10	0.107	0.041	0.100	0.046
ind11	-0.106	0.050	-0.093	0.048
ind12	-0.015	0.043	-0.074	0.044
ind13	0.032	0.048	0.020	0.048
ind14	-0.078	0.045	-0.095	0.051
size2	0.074	0.024	0.094	0.022
size3	0.118	0.023	0.165	0.022
size4	0.118	0.028	0.170	0.027
ftfract	-0.048	0.044	0.012	0.042
gpayroll	0.001	0.0004	0.0004	0.0004
dnprft	0.034	0.033	0.018	0.028
dincreasept	0.050	0.020	0.055	0.018
ddecreasept	0.028	0.024	0.044	0.021
ddownsize	-0.027	0.018	0.009	0.018
Constant	0.584	0.074	0.183	0.062

Note: OLS regression with adjusted standard errors. Data from WES. For variable definitions, see appendix.

Table 12. Effects of worker and workplace characteristics on the incidence of on-the-job and off-the-job training.

	On-the-job training		Off-the-job training	
	Estimate	s.e.	Estimate	s.e.
Worker characteristics				
Age	-0.004	0.001	-0.001	0.0002
Male	0.007	0.018	-0.003	0.006
Children	-0.043	0.015	-0.001	0.006
Immigrant	0.005	0.023	0.001	0.007
High school	0.046	0.018	0.005	0.004
More than high school	0.113	0.037	0.021	0.014
Full-time employee	-0.008	0.024	0.011	0.006
ocp2	0.012	0.031	0.005	0.015
ocp3	-0.021	0.032	-0.031	0.010
ocp4	-0.051	0.051	-0.029	0.011
ocp5	-0.044	0.036	-0.020	0.013
ocp6	-0.037	0.043	-0.025	0.012
cba	-0.014	0.017	-0.014	0.007
dcpu	0.107	0.019	0.011	0.005
dtech	0.075	0.025	0.010	0.008
Workplace characteristics				
ind2	-0.049	0.029	-0.023	0.019
ind3	0.007	0.027	-0.012	0.019
ind4	0.031	0.030	-0.035	0.018
ind5	0.043	0.033	-0.007	0.022
ind6	-0.005	0.031	-0.004	0.020
ind7	-0.0005	0.028	-0.020	0.019
ind8	0.015	0.035	-0.008	0.021
ind9	0.027	0.034	-0.034	0.018
ind10	0.092	0.035	0.019	0.020
ind11	-0.018	0.036	-0.027	0.018
ind12	0.045	0.033	-0.016	0.019
ind13	0.037	0.038	0.002	0.020
ind14	0.027	0.037	-0.023	0.020
size2	0.041	0.021	0.010	0.005
size3	0.027	0.021	0.016	0.007
size4	0.056	0.026	0.022	0.010
ftfract	-0.022	0.040	0.007	0.009
gpayroll	0.0007	0.0003	0.0003	0.0002
dnprft	0.014	0.029	0.006	0.010
dincreasept	0.023	0.018	0.001	0.006
ddecreasept	0.026	0.022	-0.005	0.006
ddownsize	-0.032	0.016	-0.005	0.025
Constant	0.353	0.068	0.074	0.025

Note: OLS regression with adjusted standard errors. Data from WES. For variable definitions, see appendix.

Appendix: Variable definitions.

Worker characteristics

age	age in 2001
male	1=yes, 0=no
children	dependent children (1=yes, 0=no)
immigrant	1=yes, 0=no
high school	highest education is high school (1=yes, 0=no)
more than high school	highest education is more than high school (1=yes, 0=no)
Full-time employee	(1=yes, 0=no) (note: full-timer if works 30 or more paid hours a week)

Occupations according to WES occupation groups:

ocp1	Managers (1=yes, 0=no)
ocp2	Professionals (1=yes, 0=no)
ocp3	Technical/Trades (1=yes, 0=no)
ocp4	Marketing/Sales (1=yes, 0=no)
ocp5	Clerical/Administrative (1=yes, 0=no)
ocp6	Production workers with no trade/certification, operation and maintenance (1=yes, 0=no)
cba	member of a union or covered by a collective bargaining agreement (1=yes, 0=no)
dcpu	using computer at work (1=yes, 0=no)
dtech	other technology used at work (1=yes, 0=no)

Workplace characteristics

Industry according to WES industry codes:

ind1	Forestry, mining, oil, and gas extraction (1=yes, 0=no)
ind2	Labour intensive tertiary manufacturing (1=yes, 0=no)
ind3	Primary product manufacturing (1=yes, 0=no)
ind4	Secondary product manufacturing (1=yes, 0=no)
ind5	Capital intensive tertiary manufacturing (1=yes, 0=no)
ind6	Construction (1=yes, 0=no)
ind7	Transportation, warehousing, wholesale (1=yes, 0=no)
ind8	Communication and other utilities (1=yes, 0=no)
ind9	Retail trade and consumer services (1=yes, 0=no)
ind10	Finance and insurance (1=yes, 0=no)
ind11	Real estate, rental and leasing operations (1=yes, 0=no)
ind12	Business services (1=yes, 0=no)
ind13	Education and health services (1=yes, 0=no)
ind14	Information and cultural industries (1=yes, 0=no)
size1	1-19 employees
size2	20-99 employees
size3	100-499 employees
size4	500 employees or more
ftfract	full-time employees (as a fraction of total # of employees)
gpayroll	gross payroll per employee (in thousands of $)
dnprft	non-profit organization (1=yes, 0=no)
dincreasept	profits increased between 2000-2001 (1=yes, 0=no)
ddecreasept	profits decreased between 2000-2001 (1=yes, 0=no)
ddownsize	company decrease (1=yes, 0=no)