Persistence in work-related training: evidence from the BHPS, 1991-1998

Sousounis, Panos and Bladen-Hovell, Robin

March 2008

Persistence in the determination of work-related training: evidence from the BHPS, 1991-1998*.

Panos Sousounis†
Keele University
Centre for Economic Research

Robin Bladen-Hovell
Keele University
Centre for Economic Research

[Draft: March 2008: Do not quote without the authors' permission]

Abstract

In this paper we investigate the role of workers' training history in determining current training incidence. The analysis is conducted on an unbalanced sample comprising information on approximately 5000 employees from the first seven waves of the BHPS. Our methodology utilizes a two-step dynamic probit model developed by Orme (2001) which allows for unobserved heterogeneity and formal modelling of initial conditions. The results suggest that prior training experience is a significant determinant of a worker's participation in a current training episode comparable with other formal educational qualifications. State dependence in the model accounts for 53% of the probability of training the current period, conditional on having experienced some form of work-related training in the previous period. For women, however, the corresponding figure is lower at approximately 38% suggesting substantially greater state dependence among male workers.

Keywords: Training; state dependence; dynamic probit
JEL codes: J24; C23.

---

* We are grateful to Gauthier Lanot for helpful comments and suggestions and Chris Orme and Wiji Arulampalam for helpful remarks.
† Address for correspondence: School of Economic & Management Studies, Keele University, Keele, ST5 5BG; e-mail: p.sousounis@econ.keele.ac.uk

1 Introduction

In recent years a broad consensus has emerged concerning the role of human capital for the determination of productivity and other economic outcomes for the individual. There is a substantial literature demonstrating the relationship between education and wage or income determination (see, for example, Blundell *et al* (1995) and almost as strong a basis for viewing productivity at the firm-level and human capital as equally well-established (see Black and Lynch (1996), Dearden (2005)). At the macro-level, human capital appears to be considered as an important source of aggregate growth and although there is a question mark against the magnitude of the effect it is treated as a central plank in the Lisbon Strategy that is designed to meet the European aspiration of becoming "the most competitive and dynamic knowledge-based economy in the world".

Although much of the discussion that has taken place with respect to human capital has focussed upon the role of education and educational attainment, it is generally well-recognized that training – on-the-job or otherwise – has a substantive part to play in the process. Indeed it may be argued that the role of training becomes increasing important as the pace of technological or organisational change in the workplace increases. Knowledge and skills acquired in formal education or from previous training episodes rapidly depreciate and become outmoded in this type of environment, requiring workers to engage continually in an ongoing process of skills acquisition.

In the existing literature these issues are invariably addressed in the context of a static framework, albeit a static framework that may extend across several years in calendar time and which may involve multiple training episodes. In the current paper we adopt an alternative approach and investigate whether previous experience of training is itself an important determinant for the incidence of training in the current period. In other words, the focus of the current paper is on whether state dependence is an important characteristic of training alongside the usual explanatory variables that reflect individual and workplace characteristics. In order to address this issue we examine the determinants of work-related training-incidence within a panel dataset comprising the first seven waves of the British Household Panel Survey, 1991 – 1997.

Naturally, once we allow an individual's current training-incidence to depend upon previous training experience we introduce a range of additional problems into the analysis. These issues most notably relate to the potentially non-trivial problem associated with the treatment of initial conditions in the data and how to deal unobserved heterogeneity. In the current paper we address both of these issues using a two-step developed by Orme (2001) which allows us estimate the degree persistence in the determination of training for men and women.

The structure of the paper is as follows. In section 1 of the paper, we describe the background to the study and provide a brief review of the background literature. The review is partial and not intended to be exhaustive but rather indicates the conventional wisdom insofar as the determinants of training are concerned. This is followed in section 2 by an outline of the econometric model and a discussion of the unobserved heterogeneity and initial conditions problem. The data used in the study are described in section 3 of the paper followed in section 4 by a discussion of the main results. The paper concludes with a brief summary and concluding comments.

2 Background

Although an extensive literature has developed in relation to training, most studies have been concerned with the evaluation of government sponsored training schemes and the role of formal educational attainment for employment outcomes (for a non-technical review of this literature see, for example, de la Fuente 2002). Work-related training, by comparison, has attracted considerably less attention with the evidence adduced by the early literature for the determinants of training well-documented by Blundell et al (1995) and OECD (2003).

Here the conventional wisdom for the UK suggests that the probability of participating in work-related training is higher among individuals with a record of prior educational attainment, men rather than women, non-minority and younger workers; see, for example, Blundell 1995 and the papers referenced therein. Work-related training is also influenced by the characteristics of the job and the workplace, increasing in large firms, the public sector and among workers who are employed full-time, unionised (Boheim and Booth (2004) report a positive impact for unions on training in Great Britain), further along the hierarchical career-ladder and working in industries that are growing or experiencing rapid technological change. In terms of outcome, training has been associated with a positive wage effect with consistently higher wages for those who train (Blundell et al 1999), and improvements in firm-level productivity and competitiveness Black and Lynch (1996), Dearden et al (2005) and Blundell et al (1999).

Although presented as the conventional wisdom it must be acknowledged that doubt remains over many of these effects. Simpson and Stroh (2002), for example, find that for the US, women receive more training than men: Green and Zanchi (1997) also report that participation in training was equalised between men and women in Britain during the 1990s. In an examining the determinants of training among Australian workers, Almeida-Santos and Mumford (2004) do not finding strong evidence of a positive link between unions and training in their sample. Research, in other words, is still ongoing.

However, despite the extensive nature of this literature there appears to have been little discussion of the possibility of persistence effects in the determination of training[1]. In many respects this is surprising. The link between training and prior formal educational attainment identified elsewhere in the literature suggests that training builds upon previously acquired skills and knowledge; if formal education and training are both part of the skills acquisition process the natural presumption would be that previous training experience is also a determinant of current training. Equally, training is an investment – for the individual and for the firm: if there are costs of adjustment associated with training we might expect to see training spread over time. Finally, all of the available evidence suggests that training is a process whereby workers' depreciating skills are updated and enhanced. But "training opportunities" are unevenly distributed across the workforce in which case prior experience of training provides an additional factor that effectively discriminates between workers further.

[1] Indeed the OECD (2003) review of the subject contains no mention of persistence effects whatsoever.

3 The model

Training incidence is modelled here as an unobserved effect, or latent variable model, where a categorical variable taking the value of 1 if the individual undertakes any work-related training in the past 12- months and 0 otherwise, is observed when the continuous latent variable y^* crosses the zero threshold. Hence the model is of the form (following the exposition in Arulampalam *et al*, 2000, where the authors test for state dependence in the incident of unemployment using the same approach):

$$y_{it}^* = x_{it}^{'}\beta + \xi y_{it-1} + \varepsilon_{it}, \quad y = 1[y^* > 0], i = 1, \dots, N, t = 1, \dots, T_i \qquad (1)$$

The latent variable y^* can be interpreted as the individual's propensity to train, x is a vector of observable characteristics affecting y^*, β is a vector of coefficients associated with those characteristics and ε is the idiosyncratic error term. By including the term, y_{it-1} the latent variable y_{it}^* is modelled as a function of the training experience of the individual in the previous period. This formulation enables to test for true state dependence in work-related training.

Caution should be exercised in modelling state dependence because a positive sign for the coefficient ξ may result from spurious correlation. As argued in Heckman (1981a, 1981b) this problem arises from so-called unobservable heterogeneity, in our case the inability to account for unobservable individual characteristics that influence the propensity of an individual to participate in work-related training.

In modelling unobserved heterogeneity we begin by assuming that the subject-specific heterogeneity is time-invariant and thus that the error term in (1) follows a one-way error components structure which can be written as

$$\varepsilon_{it} = \alpha_i + u_{it}. \qquad (2)$$

where α_i denotes the subject-specific unobservable effect and u_{it} is a random error. Assuming that $u_{it} \sim IID(0, \sigma_u^2)$, and that the u_{it} are independent of the elements of x_{it}

for all i, and t, then a standard random effects probit model can be used for estimation.

To marginalise the likelihood function and obtain consistent estimates of β we also need to assume that α_i is independent of the u_{it} and the x_{it} and $\alpha_i \sim IID(0, \sigma_\alpha^2)$. The latter is a strong assumption and if it does not hold then β will reflect some of the effect of the unobservable individual heterogeneity, a problem referred to in the literature as the incidental parameters problem.

Chamberlain (1984) proposed a procedure for relaxing the assumption of independence between α_i and the time-varying element, x_{it}. He suggested specifying a distribution for α_i conditional on $x' = x_1, \ldots, x_T$[2] which can be written as

$$\alpha_i = \gamma_0 + \gamma_1' \dot{x}_i + \gamma_i, \tag{3}$$

where it is further assumed that $\gamma_i \sim IN(0, \sigma_\gamma^2)$, that γ_i is independent of x_{it} and that u_{it} for all i and t. In principle, the vector $\dot{x}_i$ could comprise of means or lags and/or leads of the time-varying covariates. When the coefficients of γ_i associated with the time-invariant elements of x_{it} are set equal to zero and absorbing the constant γ_0 into β, model (1) becomes

$$y_{it}^* = x_{it}' \beta + \xi y_{it-1} + \gamma_1' \dot{x}_i + \gamma_i + u_{it}, \tag{4}$$

which can be computed by estimating T cross sectional probit specifications by maximum likelihood where $x_1, \ldots, x_T$ are included for each T.

If we assume that the distribution of the unobserved effect conditional on $x' = x_1, \ldots, x_T$ is linear in the means of $x_1, \ldots, x_T$, equation (4) is the standard random effects probit model with the vector of means of the time-varying individual

[2] In the linear case, the regression function for α_i given $x' = x_1, \ldots, x_T$ would most likely be some non-linear function but a minimum mean-square error linear predictor could be specified and hence the unobserved effect could be decomposed to that linear projection and an orthogonal residual term. In the non-linear case the rather restrictive assumption that the regression function $E(\alpha|x)$ is in effect linear should be imposed.

characteristics $(\bar{x}_i)$ as an added regressor. Hence, with a slight notational change, we obtain

$$y_{it}^{*} = x_{it}^{'}\beta + \xi y_{it-1} + \gamma_1^{'}\bar{x}_i + \gamma_i + u_{it}. \quad (5)$$

where the correlation between two successive error terms ε_{it} and ε_{it-1} is given by

$$corr(\varepsilon_{it}, \varepsilon_{it-1}) = \frac{\sigma_\alpha^2}{\sigma_\alpha^2 + \sigma_u^2}. \quad (6)$$

A further problem that arises in the analysis of dynamic panels is the treatment of the initial observation, y_{i0} when experimental data is not used. In particular, when the start of the stochastic process that generates the data does not coincide with the beginning of the sample, the data will suffer from correlation between the initial observation and the unobserved effect.

In our case, the great majority of individuals sampled by BHPS have been active in the labour market prior to the initial wave with the result that their propensities to engage in work-related training could be influenced by either true state dependence and/or unobserved factors. Various solutions to this initial conditions problem are suggested in the literature. Heckman (1981b), for example, has proposed a two-step procedure which is widely applied in the literature. Heckman's procedure involves specifying a reduced-form equation for the initial observation

$$y_{i0} = \zeta' z_i + v_i, \qquad var(v_i) = \sigma_v^2 \quad \text{and} \quad corr(\alpha_i, v_i) = \rho, \quad (7)$$

where the elements of z_i are strictly exogenous. The vector z includes contemporaneous to period zero variables, presample information influencing the probability of training in period zero and a vector of means, $\bar{x}_i$. In order to account for a non-zero ρ, a linear specification in terms of orthogonal error components is defined

$$v_i = \theta\alpha_i + u_{i0}, \quad (8)$$

where $\theta = \frac{\rho\sigma_v}{\sigma_\alpha}$ and $var(u_{i0}) = \sigma_v^2(1-\rho^2)$. Assuming that y_{i0} is uncorrelated with u_{it} and that u_{i0} is uncorrelated with x_{it} for all i and t, this yields a system of equations (9a) and (9b)

$$y_{it}^* = x_{it}^{'}\beta + \xi y_{it-1} + \gamma_1^{'}\bar{x}_i + \gamma_i + u_{it} \qquad i = 1, \dots, N, t = 1, \dots, T_i \qquad (9a)$$

$$y_{i0}^* = \zeta^{'} z_i + \theta\alpha_i + u_{i0} \qquad i = 1, \dots, N, t = 0. \qquad (9b)$$

Heckman (1981b) shows that when the latent variable follows an independent normal distribution conditional on the unobserved effect, the likelihood can be marginalized with respect to α and hence the likelihood function for model (9) is derived.

Orme (2001) suggests an alternative two-step approach for the initial conditions problem which is conveniently simpler. Orme's method is an approximation for small values of ρ and follows from Heckman's standard sample selection correction method. Orme proposal incorporates a correction term in the conditional model to account for the correlation between the unobserved heterogeneity and the initial observation. He has shown that under appropriate distributional assumptions, asymptotically valid results for estimation and inference can be obtained and that even though the estimator is local to zero, it can perform well even in cases where the correlation between the random effect and the initial conditions is fairly strong[3].

As in the Heckman's proposal, Orme's two step estimator requires that a reduced-form equation for the initial observation be specified. Thus, as before, we define:

$$y_{i0} = \zeta^{'} z_i + \nu_i, \qquad var(\nu_i) = \sigma_\nu^2 \text{ and } \qquad corr(\alpha_i, \nu_i) = \rho \qquad (10)$$

However, the specification for a non-zero ρ is different in this case and takes the form

$$\alpha_i + \vartheta\nu_i + \omega_i, \qquad (11)$$

[3] For a further investigation of alternative dynamic probit estimators, see A. Miranda (2007), "Dynamic Probit Models for Panel data: A Comparison of Three Methods of Estimation", paper presented to the 2007 UK Stata Users Group Meeting, September.

where $\vartheta = \frac{\rho\sigma_\alpha}{\sigma_v}$ and $var(\omega) = \sigma_\alpha^2(1-\rho^2)$. Substituting into the conditional model, we obtain

$$y_{it}^* = x_{it}^{'}\beta + \xi y_{it-1} + \gamma_1^{'}\bar{x}_i + \vartheta v_i + \omega_i + u_{it},\ i = 1, \ldots, N, t = 1, \ldots, T_i \quad (12)$$

Orme (2001) notes two points here. First, in equation (12) there are two random effects, namely, v_i and ω_i. Secondly, if (v_i, ω_i) follow a bivariate normal distribution, $E(\omega_i|v_i) = 0$ but $E(v_i|y_{i0}) = h_i$ where $h_i = (2y_{i0} - 1)\phi(\zeta^{'}z_i)/\Phi[(2y_{i0} - 1)\zeta^{'}z_i]$ by construction. Given that u_{it} are assumed orthogonal to the regressors, if v_i is replaced by the conditional expectation, h_i, ω_i will be the random component in a standard random effects probit model where h_i is included as an additional regressor.

The drawback of this estimator is that ω_i is heteroscedastic, with

$$var(\omega_i|y_{i0}) = \sigma_\alpha^2\left(1 - \rho^2 \frac{\phi(\zeta' z_i)}{\sqrt{\Phi(\zeta' z_i)\Phi(-\zeta' z_i)}}\right) \quad (13)$$

However, using Monte Carlo simulations, Orme (2001) has shown that for the dichotomous random effects model the procedure corrects the standard maximum likelihood estimates for the impact of past experience.

In summary, we apply the procedure by first estimating the reduced-form equation (10) by a simple probit, obtaining the 'generalized residual',h_i, which we then incorporate as a regressor in the random effects model (12). Equation (12) in turn embodies a lagged term and is estimated by maximum likelihood and takes the initial observation as exogenous.

4 The data

For the purpose of the current exercise we utilize data from the first seven waves of the British Household Panel Survey (BHPS hereafter), a longitudinal survey of randomly selected households in Great Britain. The first wave of the BHPS was conducted between September and December 1991 and annually thereafter[4]. The sample comprises men and women of working age who are in employment as employees in either the public, private or not-for-profit sectors[5]. Thus the sample excludes self-employed individuals, the unemployed, those in full time education and members of the armed forces. The panel is unbalanced. All individuals are present and interviewed in the first wave (1991) but are subsequently allowed to drop out of the sample as a result of missing information, attrition or having moved out of scope. Individuals were not allowed to enter or re-enter the sample after the first wave[6]. In a complementary study, a balanced sample was employed, based upon those individuals for whom complete BHPS histories are available. The main findings reported here remain unaltered in this case.

Over our sample period, the BHPS contains two variables that relate to an individual's participation in training during the twelve months prior to the interview date. The first of these variables records the incidence of formal on-the-job training undertaken as part of the individual's present employment[7] whilst the second variable records any other education or training that was undertaken that enhances skills for current or future employment. The training referred to in this latter respect is, at least potentially, work-related, excluding any education or training undertaken as a pastime, hobby or solely for general interest. In the current analysis we combine both variables in our definition of work-related training[8].

The distribution of training incidence across the seven waves for both men and women is shown in Table 1. In 1991, just over 45% of female employees in the sample reported that they had undertaken some work-related training in the previous 12-month period: for men the corresponding figure was just over 48%. Figures for subsequent waves are lower although it should be noted that, with the exception of

[4] For more details see Taylor, M.F et al (2006).

[5] The not-for-profit sector employees in the data are rather limited and likely to cause problems of micro-numerocity if accounted for separately. Since not-for-profit firms operate in a similar fashion to private firms with regards to profit maximisation, the not-for-profit employees are regarded as private firm employees and hence they are absorbed in the private sector employees.

[7] In Wave One, only the employed were asked this. At Wave Two, this was extended to all currently working. The scope of the question was widened to include education or training courses.

[8] The relevant questions in the 1991 BHPS D23 and E17.

Wave 7 for men, training incidence generally increases in the survey for men and women alike from the 1992 onwards. The raw data also appears to offer little support for the hypothesis that men receive more training than women although in this context it should be noted that head-count measures of the sort employed here are an incomplete measure of participation in training programmes with alternative volume measures representing possibly better indicators for this issue.

Table 1: Training incidence for men and women in the 12-months prior to interview

	Wave (year)						
	Wave 1 (1991)	**Wave 2 (1992)**	**Wave 3 (1993)**	**Wave 4 (1994)**	**Wave 5 (1995)**	**Wave 6 (1996)**	**Wave 7 (1997)**
Females							
Training incident (%)	45.2	38.2	38.5	40.9	40.1	43.6	43.8
n	2500	1949	1745	1669	1542	1505	1421
Males							
Training incident (%)	48.3	39.7	40.9	41.5	42.6	43.8	37.9
n	2468	1891	1639	1542	1453	1403	1347

A potentially more significant problem with the head-count measure of training is that training episodes may extend across waves with the result that our analysis would overstate the effect of training. This problem is not, of course specific to training and may also be found, for example, in studies of state dependence among the unemployed (see Arulampalam xxxx). In addition, since the survey is conducted retrospectively, some errors of recollection are also to be expected. This problem, however, is likely to smaller in relation to the recollection of an event occurring than with respect to the detail of the event, such as length and nature of the training episode.

In modelling work-related training we include a set of variables that reflect individual characteristics such as age, indicators of prior educational attainment, race, and occupation, employment and employer characteristics such as job permanency, part-time, full-time status, hierarchical position within the firm, trade union presence and firm size together with an indicator of training history. In addition, a set of variables recording past information, including the socio-economic and personal characteristics of the respondent's father and pre-sample information on the respondent, is utilised in the estimation of the reduced-form equation for the initial conditions. Finally, the relationship is estimated separately for men and for women. Summary statistics for the main variables in the paper are given in Table 2.

Table 2: Summary Statistics

	Men		Women	
	mean	sd	mean	sd
Training	0.444	0.497	0.436	0.496
Age	38.25	10.42	38.69	10.45
Race	0.032	0.175	0.026	0.161
Higher degree	0.028	0.165	0.016	0.126
First degree	0.113	0.316	0.101	0.301
Teaching qualification	0.014	0.119	0.043	0.202
Other higher qualification	0.259	0.438	0.141	0.348
Nursing qualification	0.002	0.048	0.039	0.193
GCE A-level	0.154	0.360	0.109	0.312
GCE O-level or equivalent	0.195	0.396	0.282	0.450
Commercial qf no O-levels	0.002	0.044	0.057	0.231
CSE 2-5, Scottish grade 4-5	0.054	0.226	0.034	0.181
Apprenticeship	0.026	0.158	0.004	0.064
Other qualification	0.006	0.076	0.008	0.089
No qualification	0.147	0.354	0.167	0.373
Part-time	0.035	0.184	0.356	0.479
Private sector	0.769	0.426	0.584	0.493
Trade union coverage	0.534	0.498	0.556	0.497
Mining	0.377	0.485	0.143	0.350
Construction	0.059	0.236	0.007	0.083
Wholesale, retail, hotels, transport	0.226	0.418	0.242	0.428
Financial services, real estate	0.120	0.325	0.133	0.340
Public administration, education, health & social	0.181	0.385	0.430	0.495
Other Community, Social	0.021	0.142	0.041	0.198
Agriculture	0.015	0.122	0.004	0.065
Professional	0.088	0.283	0.026	0.159
Managerial and technical	0.324	0.468	0.323	0.468
Skilled non-manual	0.137	0.343	0.389	0.488
Skilled manual	0.309	0.463	0.079	0.271
Partly skilled	0.121	0.326	0.142	0.349
Unskilled	0.021	0.144	0.041	0.199
Establishment < 50	0.387	0.487	0.521	0.500
Establishment 50-99	0.141	0.348	0.125	0.331
Establishment 100-499	0.271	0.445	0.213	0.409
Establishment 500+	0.200	0.406	0.141	0.348

The sample is almost equally balanced between men and women and the average age is 38 years old irrespective of gender. Men on average tend to be better qualified and dominate the skilled manual group and professional groups. As might be expected more women are employed part-time and are more strongly represented in the public administration, education and health sectors. A cursory examination of the incidence of training across the occupational groups illustrates the conventional finding that training is heavily skewed away from the unskilled.

Table 3 Training Participation across occupational groups (%)

	All	Males	Females
Professional	58.5	56.1	66.2
Managerial & Technical	58.4	54.9	61.7
Skilled (non-manual)	41.7	54.5	37.3
Skilled (manual)	33.6	33.2	34.7
Partly skilled	25.7	25.5	25.9
Unskilled	20.2	26.1	17.6

5 Econometric Results

The preferred estimates for the random effects probit model for men and women, where state-dependence and initial conditions effects are allowed for are presented in the first two columns of Table 4[9]. An alternative specification, excluding state-dependence and initial conditions effects is presented in Columns [4] and [5] for comparison purposes. Estimates for the reduced-form initial conditions are given in Appendix 1 and include a set of pre-sample characteristics together with relevant current period variables. Discussion of these estimates is withheld as they predominantly serve as a step towards estimation of the random effects probit model for subsequent waves.

[9] Estimation was performed using STATA 9.1, StataCorp (2006). The random effects probit estimator uses a twelve-point quadrature approximation for the likelihood integral.

A dynamic term is included in the random effects probit models to control for state-dependence. The proportion of the variance explained by unobserved individual heterogeneity varies between the base model and the comparison model from 20% to 36% for women and from 18% to 37% for men. All models were estimated by including time means of the time varying covariates in line with Chamberlain's (1984) procedure, to control for possible correlation between the explanatory variables and the random effect. Year dummies were also included to pick up macroeconomic effects, as were regional dummies to account for any regional disparities. The remaining of this section considers the estimates from the random effects probit models for both men and women.[10]

The state-dependence effect in the random effects model is highly significant and of comparable magnitude to an individual having attained an A-level in prior education, suggesting a substantial effect on the probability of engaging in work-related training both for men and for women. State-dependence, as evidenced by the magnitude of the coefficient of the lagged term in the model, appears to be smaller for women suggesting that the effect of training history is more pronounced in the case of male employees[11].

The coefficient on the generalized residual term from the reduced-form equation for the first year in the random effects models is also found to be highly statistically significant for men and women, indicating a strong rejection of the hypothesis that initial conditions are exogenous to the training decision. The estimates from the comparison models, which exclude state-dependence and treat the initial conditions as exogenous appear also to consistently overestimate the impact of all covariates in our model for both males and females.

Turning to the conventional determinants, age appears to have a statistically significant, inverse U-shaped profile for women with training increasing to age 41 before declining. Although this may relate to interrupted employment spells for women we could find no affect associated with dependent children. In contrast, age

[10] Note that there is no restriction on the size of the coefficient imposed in a probit model, as would be required for stationarity in a time-series model.

[11] Models including a two-year lag were also estimated with substantially the same effect.

has a statistically insignificant effect in the model for male employees, suggesting that the training profile for men is flat over their working life. Educational qualifications on the other hand are found to have a positive and statistically significant impact for men and women alike with higher qualifications being associated with a greater probability of training. Racial background (white: non-white) is also found to have a

Table 4. Coefficient Estimates of the Random Effects Probit Model of Work-Related Training for Men and Women

	Random Effects Probit Models (1991 Initial Conditions)		Comparison Models (excluding state-dependence and assuming exogenous initial conditions)	
	Females [1]	**Males [2]**	**Females [3]**	**Males [4]**
Variable				
Intercept	-3.4423 [6.09]	-0.6696 [1.20]	-2.9862 [5.52]	-0.1913 [0.35]
Lagged dependent variable				
Trained *t-1*	0.4188 [9.01]	0.5933 [12.6]		
Personal characteristics (current period)				
Age	0.0569 [3.51]	-0.0264 [1.72]	0.0459 [2.84]	-0.0223 [1.33]
Age ^{2}	-0.0007 [3.96]	0.0001 [0.65]	-0.0006 [3.34]	0.0000 [0.10]
Race (white)	0.2481 [1.76]	0.3370 [2.39]	0.1602 [1.07]	0.4202 [2.68]
Marital Status (single)	0.0452 [0.85]	-0.1693 [3.00]	0.0240 [0.45]	-0.1860 [2.28]
Responsible for dependent child under 12	-0.1037 [1.92]		-0.1490 [2.74]	
Social class				
Professional occupation	0.4742 [2.68]	0.3228 [1.81]	0.6632 [3.75]	0.2330 [1.33]
Managerial & Technical occupation	0.3841 [3.00]	0.4004 [2.38]	0.5625 [4.47]	0.3162 [1.94]
Skilled non-manual occupation	0.3184 [2.60]	0.4232 [2.53]	0.4937 [4.09]	0.3595 [2.22]
Skilled manual occupation	0.1568 [1.14]	0.2106 [1.31]	0.3262 [2.45]	0.0890 [0.58]
Partly skilled occupation	0.1737 [1.39]	-0.015 [0.13]	0.2656 [2.18]	-0.1113 [0.70]
Highest Educational Qualification				
Higher degree	0.5599 [2.87]	0.3227 [2.23]	0.7372 [3.77]	0.4927 [2.89]
First degree	0.6749 [6.28]	0.6196 [5.92]	0.8639 [7.72]	0.9348 [8.01]
Teaching qf.	1.0396 [7.60]	0.7841 [4.18]	1.2988 [9.10]	1.0877 [4.92]
Other higher qf.	0.6464 [7.29]	0.6082 [7.40]	0.7775 [8.60]	0.8575 [9.48]
Nursing qf	0.5911 [4.14]	0.5685 [1.49]	0.6031 [4.23]	0.9134 [2.07]

GCE A levels	0.4816 [4.92]	0.3009 [3.37]	0.5817 [5.79]	0.4453 [4.44]
GCE O levels or equivalent	0.1582 [2.01]	0.2685 [3.19]	0.2231 [2.73]	0.4078 [4.32]
Commercial qf / No O levels	0.1725 [1.53]	-0.0299 [0.07]	0.1551 [1.29]	-0.0331 [0.06]
CSE Grade 2-5 / Scottish Grade 4-5	0.0070 [0.05]	-0.0184 [0.15]	-0.0224 [0.14]	0.0753 [0.55]
Apprenticeship	0.3865 [1.07]	0.1321 [0.86]	0.3191 [0.86]	0.2298 [1.31]
Other qualifications	-0.0839 [0.30]	-0.5497 [1.44]	-0.1486 [0.47]	-0.3926 [1.03]
Characteristics of current job/employer				
Private Sector	-0.1781 [2.31]	-0.2071 [2.62]	-0.2440 [3.27]	-0.2338 [2.80]
Permanent position	0.2459 [2.79]	0.2176 [1.88]	0.2848 [3.64]	0.2323 [2.28]
Working Part Time	-0.2393 [4.67]	-0.4387 [3.38]	-0.3099 [6.19]	-0.4447 [3.80]
Trade union coverage in the workplace	0.2186 [4.15]	0.1883 [3.82]	0.2477 [4.80]	0.2196 [4.21]
Size of employing organization (manpower)				
More than 25 / 50 to 99 (small)	0.0376 [0.60]	0.1137 [1.87]	0.0680 [1.12]	0.1364 [2.24]
100 to 499 (medium)	0.0783 [1.44]	0.1723 [3.30]	0.0995 [1.84]	0.1757 [3.22]
500 or more (large)	0.1301 [2.03]	0.2166 [3.67]	0.2155 [3.40]	0.2847 [4.57]
Managerial position	0.1456 [2.19]	0.1088 [1.76]	0.2098 [3.19]	0.1440 [2.22]
Supervisor/foreman	0.1313 [2.36]	0.1311 [2.43]	0.1337 [2.49]	0.1548 [2.84]
Generalized residual from the initial condition probit	0.2443 [7.66]	0.2647 [8.41]		
Proportion of variance of unobserved heterogeneity in total unexplained variance (r)	0.2110	0.1818	0.3526	0.3763
Log-likelihood	-3856.0149	-3844.5654	-4945.5679	-4764.9497
Log-likelihood when $r = 0$	-3903.7850	-3876.8488	-5240.8230	-5085.1742
NT	7228	7037	9099	8432
N	1505	1454	1845	1704

Notes: All models include regional dummy variables, time dummies and dummies for the Standard Industrial Classification of the current job. In addition, all RE probit models include time means of the time-varying covariates to allow for correlation between the latter and the unobserved heterogeneity and allow for endogenous initial conditions. Absolute t values in brackets.

positive and statistically significant impact for men but not for women, which could be an indication of discrimination operating against non-white males or may simply reflect the supply-side effect that male employees from among the ethnic minorities invest less in human capital.

Among the workplace and employer characteristics, little evidence is found that the size of the organization has an effect on the probability of training for women, with only the large firms having a marginally significant positive impact. For men the story is different with evidence that training incidence is consistently greater among larger enterprises. Private sector affiliation on the other hand reduces training intensity for men and women alike, as does part-time work, and temporary work. Trade union coverage is also associated with a significantly positive coefficient.

Men and women in less skills-intensive occupations also appear less likely to participate in work-related training. Hierarchical effects also appear to be present with the model suggesting a significantly positive effect for both men and women in professional, managerial and skilled non-manual occupations. Supervisory and managerial roles increase the likelihood of training for women similarly.

6 Predicted probabilities

The random effects probit models may be used to calculate work-related training probabilities for men and women that may be compared to the raw aggregate probabilities. These calculations are detailed in Table 5a in the case of men and Table 5b for women. In each Table the first panel presents raw data probabilities of experiencing training in the current period, conditional upon the individual having experienced a training episode in the 12-month period prior. The second panel records the predicted probabilities from the random effects probit model. In this calculation the effect of state dependence is calculated as the difference between the predicted probability obtained by setting the individual unobserved effect to zero and conditioning, first on the individual having participated in work-related training in the previous period and second, on the individual not having participated in work-related training in the previous period. The calculations therefore show the probability of a randomly chosen individual being observed participating in any form of work-related training in the current period; holding characteristics constant, and conditional upon

Table 5a Raw Data Probabilities and Predicted Probabilities for Men

	Wave 2 [1992]	Wave 3 [1993]	Wave 4 [1994]	Wave 5 [1995]	Wave 6 [1996]	Wave 7 [1997]
Raw Data Probabilities:						
(1) Training the previous period	0.6239	0.6578	0.6553	0.6775	0.6726	0.6071
(2) No training the previous period	0.1818	0.2490	0.2541	0.2564	0.2395	0.2103
(3) (1)-(2)	0.4421	0.4088	0.4012	0.4211	0.4331	0.3968
Predicted Probabilities holding characteristics constant						
(4) Trained at *t-1*	0.4808	0.5220	0.5133	0.5255	0.5285	0.4604
(5) Not trained at *t-1*	0.2606	0.2952	0.2878	0.2983	0.3009	0.2442
(6) State Dependence	0.2202	0.2268	0.2255	0.2272	0.2276	0.2162
As % of (3)	49.8	55.4	56.2	53.9	52.5	54.4

Table 5b Raw Data Probabilities and Predicted Probabilities for Women

	Wave 2 [1992]	Wave 3 [1993]	Wave 4 [1994]	Wave 5 [1995]	Wave 6 [1996]	Wave 7 [1997]
Raw Data Probabilities						
(1) Training the previous period	0.5843	0.6470	0.6980	0.6627	0.6833	0.6572
(2) No training the previous period (%)	0.2007	0.2217	0.2280	0.2224	0.2738	0.2744
(3) (1)-(2)	0.3836	0.4253	0.4700	0.4403	0.4095	0.3828
Predicted Probabilities holding characteristics constant						
(4) Trained at *t-1*	0.4210	0.4298	0.4486	0.4584	0.5002	0.5033
(5) Not trained at *t-1*	0.2682	0.2757	0.2918	0.3004	0.3379	0.3407
(6) State Dependence	0.1528	0.1541	0.1568	0.1580	0.1623	0.1626
As % of (3)	39.8	36.2	33.3	35.8	39.6	42.4

having participated or not in work-related training in the previous period. The difference is reported in row (6) of each table. The results suggest that for men, state dependence on average accounts for approximately 53% of the probability of training the current period, conditional on having experienced some form of work-related training in the previous period. The estimates also appear stable and consistent across the BHPS waves. For women the corresponding figure is considerably lower, at approximately 38%, suggesting substantially greater state dependence among male workers.

7 Summary and Conclusions

This study has examined whether an individual's participation in work-related training is characterised by state dependence, with current participation depending in part upon the worker having previously participated in a training episode. Training participation is modelled as a dynamic random effects probit model where the effects of unobserved heterogeneity and initial conditions are accounted for in a fashion consistent with methods proposed by Chamberlain (1984) and Orme (2001) respectively. Within this framework, the effects of state dependence on the probability of training are captured by the inclusion of the lagged outcome variable.

The evidence suggests that not only does state dependence exist for training in the UK but that the effect is important and of a magnitude comparable with that associated with formal educational qualifications. Such a relationship clearly has important implications for labour market behaviour and outcomes. State dependence in training and the link between wages and training and productivity and training offers a deviation-amplifying mechanism that would underpin wage dispersion and differentiated growth among individual workers and firms.

References

ALMEIDA-SANTOS, F., and K. MUMFORD (2004): "Employee Training and Wage Compression in Britain," Institute for the Study of Labor (IZA).

ARULAMPALAM, W. (1998): "A Note on Estimated Coefficients in Random Effects Probit Models," *The Warwick Economics Research Paper Series (TWERPS)*.

ARULAMPALAM, W., A. L. BOOTH, and M. P. TAYLOR (2000): "Unemployment Persistence," *Oxford Economic Papers*, 52, 24-50.

BLACK, S. E., and L. M. LYNCH (1996): "Human-Capital Investments and Productivity," *The American Economic Review*, 86, 263-267.

BLUNDELL, R., L. DEARDEN, and C. MEGHIR (1996): "The Determinants and Effects of Work-Related Training in Britain," *The Institute for Fiscal Studies*.

— (1999): "Work-Related Training and Earnings," *mimeo, Institute of Fiscal Studies*.

BLUNDELL, R., L. DEARDEN, and B. SIANESI (1999): "Human Capital Investment: The Returns from Education and Training to the Individual, the Firm and the Economy," *Fiscal Studies*, 20 (1), 1-24.

BOOTH, A. L. (1991): "Job-Related Formal Training: Who Receives It and What Is It Worth?," *Oxford Bulletin of Economics and Statistics*, 53 (3), 281-94.

BOOTH, A. L., and M. L. BRYAN (2002): "Who Pays for General Training? New Evidence for British Men and Women," Institute for the Study of Labor (IZA).

CHAMBERLAIN, G. (1984): "Panel Data," *Handbook of Econometrics, S. Griliches and M. Intriligator (eds)*, Amsterdam, North-Holland, 1247-318.

DE LA FUENTE, A., and A. CICCONE (2003): "Human Capital in the Global Knowledge Based Economy: Final Report for the European Commission, Dg for Employment and Social Affairs," *Luxumberg*.

DEARDEN, L., S. MACHIN, H. REED, and D. WILKINSON (1997): "Labour Turnover and Work-Related Training," *The Institute for Fiscal Studies*, London.

DEARDEN, L., H. REED, and J. VAN REENEN (2000): "Who Gains When Workers Train? Training and Corporate Productivity in a Panel of British Industries," *Working Paper No. 00/04*, Institute for Fiscal Studies.

— (2005): "The Imapct of Training on Productivity and Wages: Evidence from British Panel Data," *IFS Working Paper*, WP05/16 London.

GREEN, F., S. MACHIN, and D. WILKINSON (1999): "Trade Unions and Training Practices in British Workplaces," *Industrial and Labor Relations Review*, 52 (2), 179-95.

GREEN, F., and L. ZANCHI (1997): "Trends in the Training of Male and Female Workers in the United Kingdom," *British Journal of Industrial Relations*, 35, 635-644.

HECKMAN, J. J. (1981a): "Statistical Models for Discrete Panel Data," *in C.F. Manski and D. McFadden (eds), Structural Analysis of Discrete Data with Econometric Applications*, MIT Press, 114-78. 24

— (1981b): "The Incidental Parameters Problem and the Problem of Initial Conditions in Estimating a Discrete Time-Discrete Data Stochastic Process," *in C.F manski and D. McFadden (eds), Structural Analysis of Discrete Data with Econometric Applications*, MIT Press, 115-78.

MIRANDA, A. (2007): "Dynamic Probit Models for Panel Data: A Comparison of Three Methods of Estimation," *presented at 2007 UK stata Users Group Meeting*.

O.CONNELL, P. (1999): "Adults in Training: An International Comparison of Continuing Education and Training," *The Economics and Social Research Institute*, Dublin.

OECD (1999): "Training of Adult Workers in Oecd Countries: Measurement and Analysis," *Employment Outlook*.

— (2003): "Upgrading Workers' Skills and Competencies," *OECD Employment Outlook: Towards More and Better Jobs*, 237-296.

ORME, C. D. (2001): “Two-Step Inference in Dynamic Non-Linear Panel Data Models”, University of Manchester, *mimeo*.

TAYLOR, M. F. E., J. BRICE, N. BUCK, and E. PRENTICE-LANE (2006): "British Household Panel Survey User Manual Volume A: Introduction, Technical Report and Appendices," *Colchester: University of Essex*

.

Appendix 1 Initial Conditions Estimates

Variable	Females [1]		Males [2]	
Constant	-1.9110	[.5882]	-1.6863	[1.0582]
Personal characteristics				
Sex (Female)				
Age	.0242	[.0209]	-.0309	[.0194]
Age ^{2}	-.0004	[.0002]	.0000	[.0002]
Race (white)	-.0619	[.1814]	.0834	[.1668]
Marital Status (single)	-.0428	[.0783]	-.0503	[.0839]
Responsible for dependent child <12	.1015	[.0828]	.7464	[.4450]
Social class				
Professional occupation	.8429	[.3101]	.9374	[.2571]
Managerial & Technical occupation	.8939	[.1969]	.7217	[.2362]
Skilled non-manual occupation	.6476	[.1811]	.8600	[.2282]
Skilled manual occupation	.3369	[.2091]	.3571	[.2221]
Partly skilled occupation	.4772	[.1898]	.4217	[.2275]
Highest Educational Qualification				
Higher degree	.5125	[.3561]	.1178	[.2467]
First degree	.5125	[.3561]	.5507	[.1648]
Teaching qf.	1.2403	[.2185]	.3256	[.3166]
Other higher qf.	.6981	[.1445]	.3586	[.1111]
Nursing qf	.4733	[.1839]	.9249	[.5440]
GCE A levels	.7002	[.1462]	.3928	[.1167]
GCE O levels or equivalent	.4826	[.1148]	.2488	[.1058]
Commercial qf / No O levels	.2721	[.1444]	-.1519	[.5797]
CSE Grade 2-5 / Scottish Grade 4-5	.2129	[.1917]	.2991	[.1484]

Apprentiship	.5571	[.3978]	.3360	[.1705]
Other qualifications	.8175	[.3842]	.0178	[.4150]
Characteristics of current job/employer				
Private Sector	-.2802	[.1317]	-.2441	[.1174]
Non-Permanent position	-.1616	[.1157]	-.2728	[.1351]
Working Part Time	-.2035	[.0796]	-.3421	[.1582]
Trade union coverage in the workplace	.2583	[.0811]	.3795	[.0742]
Size of employing organization (manpower)				
More than 25 / 50 to 99 (small)	.0637	[.0930]	.1628	[.0974]
100 to 499 (medium)	.1924	[.0875]	.1719	[.0817]
500 or more (large)	.1073	[.1079]	.2820	[.0922]
Managerial position	.2525	[.1199]	.3191	[.1084]
Supervisor/foreman	.2565	[.0893]	.2457	[.0848]
Presample Information				
Father was in a (respondent age 14)				
Professional occupation	-.2234	[.2161]	-.3344	[.2184]
Managerial & technical occupation	-.1259	[.2067]	-.3401	[.2004]
Skilled non-manual occupation	-.1052	[.1903]	.0395	[.1873]
Skilled manual occupation	.1110	[.1655]	-.0672	[.1527]

Note: Weighted estimates by the BHPS cross-sectional (Wave 1) weights. Standard errors are given in parentheses.