The Impact of Work-Related Training on Employee Earnings: Evidence from Great Britain.

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Abstract

Using data from the British Household Panel Survey for the years 1998-2005, this study estimates the impact of work-related training on earnings levels. Different measures for general and specific training are constructed from available information. The analysis diverges from the standard fixed effects framework for earnings determination modelling and presents evidence in support of the predictions of the standard human capital theory with regards to training sponsoring using a random effects formulation for the earnings equation suggested by Nijman and Verbeek (1992) for controlling for attrition bias in unbalanced panels.

JEL classification: J24, J31, C23
Keywords: work-related training, human capital, earnings

I Introduction

Work-related training is a key factor of human capital formation and as such it has attracted much attention in the theoretical and empirical economic literature as well as amongst policy makers. It is widely regarded as the means by which productivity and living standards can be raised especially amongst those less skilled segments of the workforce (Ok and Tergeist, 2002).

Nonetheless, most employer-financed activity has been concentrated on those workers who possess high levels of human capital since from an investment perspective, training of this group would be more profitable (Blundell *et al*, 1999). Such practice is expected to create 'virtuous' circles for the high-skilled workers resulting in higher wages, and subsequently higher living standards and longer tenure (Gershuny, 2005) and more training opportunities due to the effects of serial persistence in the work-related training incidence. On the other hand, workers with less formal education (or less accumulated human capital) will be more likely to receive less work-related training leading them[1] to a vicious circle of skill degradation with eventual higher levels of unemployment (Keep *et al*, 2002). This effect is particularly pronounced in an economy primarily based on the tertiary sector of production where skills

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[1] This result is observable for workers with fewer formal qualifications as a group, but not necessarily for each individual one over their life cycle.

become rapidly obsolete and the workforce needs to be frequently re-trained in order to follow technological progress.

Theoretical work has concentrated on the nature of the investment decision and the sharing of costs and benefits between employers and employees (see among others Becker, 1964, Hashimoto, 1981, Acemoglu and Pischke, 1998). Empirical investigations have focused on the extent and impact of work-related training, using large individual-level data to estimate reduced-form wage equations (see among others Lynch, 1992, Booth, 1993, Booth *et al*, 2003). Much of the analysis of these effects has been limited by the unavailability of detailed information in the existing data sets as to the type and financing of the training events. The aim of this paper is therefore to provide evidence of the relationship between training and earnings based on the data collected in the rich British Household Panel Survey.

The orthodox human capital model as formulated by Becker (1962, 1964) predicts that under competitive conditions, employees will have to finance any investment in general human capital either through accepting lower wages during the training period if they are credit constrained or by meeting the training costs directly. If the nature of the training investment is deemed as specific to the firm, individuals will not be willing to finance the training since they will only be able to earn a return on their investment with the current firm. The employing firm on the other hand will be willing to finance the investment provided that the individual continues working in the firm in the post-training period – this is the only way the firm can benefit from the individuals increased productivity. However, a contract that will bind the individual with the firm in the post-training period is difficult to enforce. Such contractual difficulties will lead to the costs and benefits being shared between the two parties (Hashimoto, 1981).

Recent theoretical advances relax the assumption of perfectly competitive markets and provide conditions under which the firm will be prepared to pay for general training (Katz and Ziderman, 1990, Stevens, 1994, Loewenstein ans Spletzer, 1998, Acemoglu and Pischke, 1999, Booth and Zoega, 1999). Such conditions are termed "wage compression" meaning that the wages are artificially kept (compressed) below productivity and hence the firm can both finance general training and share some of the benefits through this compressed wage structure in both pre- and post-training period.

The results obtained here complement the existing body of evidence from different datasets and add to the evidence from the British Household Panel Survey using data from recent waves. The estimates lend support to the neoclassical theory of human capital whereby employees finance their investment in general human capital and employers finance firm-specific human capital. This claim is substantiated by evidence from alternative measures of general training.

The remainder of the paper is set out as follows. A consistent estimator for the earnings equation that accounts for self selection, suggested by Nijman and Verbeek (1992), is discussed in section II. Section III presents the data used and section IV discusses the econometric estimates. The final section, V, summarises and draws conclusions.

II A 'self-selection' consistent estimator for the earnings equation

When attrition from the panel is not random but occurs for some reason which is systematically related to the outcome variable, conditioning on observable explanatory variables is not enough to alleviate the problem of self-selection. However, the very nature of panel data allows correcting for self selection due to attrition through first-differencing, provided attrition from the sample is the result of a time-invariant unobserved component.

If subjects do not leave the panel altogether but certain observations on some variables are missing for at least some time periods (incidental truncation) the parameter estimates from the non-missing subsample will be biased. This situation is treated as a sample selection problem since data are available for a subset of the population defined by some rule – being in employment in this case. With panel data a number of individuals are expected to move from employment to unemployment in the course of the observation period and hence information on their wage offer will be missing. This differs from attrition in the sense that individuals do not disappear from the sample or move out of scope and hence dropped, but rather some variables are not observed for everyone in each time period.

The computational cost of maximum likelihood estimation, which requires the evaluation of multiple integrals, has motivated the consideration of simpler or two-step estimators (Vella, 1998). Consider the conventional, linear panel data model which allows for unobserved effects under the assumption of random sampling in the cross section dimension

$$y_{it} = \mathbf{x}_{it}\boldsymbol{\beta} + \alpha_i + u_{it}; i = 1, \dots, N; t = 1, \dots, T, \tag{1}$$

where $\mathbf{x}_{it}$ is a $1 \times L$ vector of explanatory variables and $\boldsymbol{\beta}$ is the $L \times 1$ parameter vector of interest. Asymptotic analysis is carried out assuming $N \to \infty$ and the unobserved effect, α_i, is allowed to be arbitrarily correlated with x_{it}.

Every individual is observed in the first time period, $t = 1$, but observations for some individuals may be missing in subsequent time periods thus observations are available for T_i periods for some individuals with T being the maximum possible available observations. Let $\boldsymbol{s}_i \equiv (s_{i1}, \dots, s_{iT})'$ be the $T \times 1$ vector of selection indicators where $s_{it} = 1$ if $(\mathbf{x}_{it}, y_{it})$ is observed and $s_{it} = 0$ if not, for a random sample drawn from the population.

By applying the within transformation on the available observations of the resulting unbalanced panel, the fixed effects estimator assumes the form

$$\hat{\beta}_{FE} = \left(\frac{1}{N}\sum_{i=1}^{N}\sum_{t=1}^{T} s_{it}\tilde{\mathbf{x}}_{it}'\tilde{\mathbf{x}}_{it}\right)^{-1}\left(\frac{1}{N}\sum_{i=1}^{N}\sum_{t=1}^{T} s_{it}\tilde{\mathbf{x}}_{it}'\tilde{y}_{it}\right),$$

where

$$\tilde{\mathbf{x}}_{it} = \mathbf{x}_{it} - T_i^{-1} \sum_{h=1}^{T} s_{ih}\, \mathbf{x}_{ih}, \qquad \tilde{y}_{it} = y_{it} - T_i^{-1} \sum_{h=1}^{T} s_{ih}\, y_{ih} \qquad \text{and} \qquad T_i = \sum_{t=1}^{T} s_{it}.$$

Consistency of the fixed effects estimator on the unbalanced panel is ensured by two assumptions (1) $E\left(s_{it}\tilde{\mathbf{x}}_{it}^{'}u_{it}\right) = 0$ for every t and (2) $\sum_{t=1}^{T} E(s_{it}\tilde{\mathbf{x}}_{it}^{'}\tilde{\mathbf{x}}_{it})$ be nonsingular. Since the transformed vector of explanatory variables, $\tilde{\mathbf{x}}_{it}$, depends on all of $\mathbf{x}_i$ and $\mathbf{s}_i$, the strict exogeneity assumption $E(u_{it}|\mathbf{x}_i, \mathbf{s}_i, \alpha_i) = 0$ for $t = 1, \dots, T$ is needed for assumption (1) to hold. Under this strict exogeneity assumption and given that $s_{it}\tilde{\mathbf{x}}_{it}$ is a function of $(\mathbf{x}_i, \mathbf{s}_i)$, $E\left(s_{it}\tilde{\mathbf{x}}_{it}^{'}u_{it}\right) = \mathbf{0}$ follows from the law of iterated expectations. Assumption (2) is the rank condition on the expected outer product matrix after allowing for sample selection (Wooldridge, 2002, p.579).

Verbeek and Nijman (1992) discuss the random effects estimator for the unbalanced panel. Random effects analysis hinges on much stronger assumptions in this case. Whereas the fixed effects estimator requires $E(u_{it}|x_{it}, s_{it}) = 0$, the random effects estimator requires $E(u_{it} + \alpha_i|x_{it}, s_{it}) = 0$ for consistency. That is, while in the fixed effects environment selection is allowed to operate through the individual heterogeneity (but not the idiosyncratic error), selection cannot operate either through the individual specific effect and/or the idiosyncratic error in the random effects environment (Vella, 1998). In other words, with an unbalanced panel, random effects analysis requires that selection is independent of the unobserved individual effect; in the wage equation, for example, consistency of random effects could come under question if high (or low) ability individuals are more prone to attrition (Wooldridge, 2002).

The fixed effects estimator does not require parametric assumptions about the disturbances nor the specification of a fully specified model for the selection process and has thus been proven attractive in much applied work. A different method, in the spirit of the Heckman (1979) procedure for the cross sectional case, has been employed by Ridder (1990), Nijman and Verbeek (1992) and generalised by Vella and Verbeek (1994). This procedure, which is a generalisation of the Heckman (1979) procedure to the case of panel data, involves the computation of the conditional expectation of the random components, which is subsequently included in the set of regressors in the outcome equation to provide a test for the hypothesis of non-response bias.

Following Nijman and Verbeek's (1992) exposition, and in line with tradition in the literature of training (see Booth and Bryan, 2002 and Lowenstein and Spletzer, 1998) the earnings returns from work-related training are formulated following a Mincerian wage regression of the form

$$\log w_{it} = \beta_0 + \beta x_{it} + \theta T_{it} + Y_t\delta + \alpha_i^* + \varepsilon_{it}\,;\, i = 1, \dots, N\,;\, t = 1, \dots, T, \qquad (2)$$

where $\ln w_{it}$ is the natural logarithm of the real weekly earnings of individual i at time t. Earnings (in UK sterling) are deflated using the Retail Price Index and expressed in constant 2005 prices. The vector x_{it} includes level and quadratic terms for the age of the individual in addition to other individual, job and workplace characteristics. The term α_i^*, assumed[2] $\alpha^* \sim IN(0, \sigma_{\alpha^*}^2)$ and independent of ε_{it}, captures

[2] IN refers to independent normal distribution

unobservable individual characteristics determining wages such as motivation, inherent ability and/or ambition. Individuals in the sample may switch between jobs; such occurrence is modelled via a dummy argument (1 if individual i changes jobs in the 12 month period prior to being interviewed and 0 otherwise) included in the regressors' set.

Work-related training is captured by T_{it}. The dataset allows construction of a number of proxies for general and specific training measures such as on- and off-the-job training, training with a previous employer, accredited and non-accredited training as well as proxies for the financing of training and Y_t is a vector of year specific dummy variables. The intercept term in the wage regression is expected to capture individual differences in skills; this has traditionally been the assumption in most empirical models and is also maintained here[3].

To account for possible correlation between the unobserved effect and the explanatory variables, the formulation suggested by Mundlak (1978) and Chamberlain (1984) is applied, whereby it is assumed that

$$\alpha_i^* = \bar{x}_i \mu_1 + \alpha_i, \tag{3}$$

where $\bar{x}_i$ is the time means of x_{it} and α_i is uncorrelated with x_{it}. Substituting equation (3) into (2), the model of interest emerges,

$$\ln w_{it} = \beta_0 + \beta x_{it} + \theta T_{it} + Y_t \delta + \bar{x}_i \mu_1 + \alpha_i + \varepsilon_{it}, \tag{4}$$

where the errors ε_{it} are assumed independently and identically distributed over both N and T and independent of all x_{js} . It is further assumed that $\alpha_i \sim N(0, \sigma_\alpha^2)$ and independent of ε_{jt} and x_{jt} for all i, j and t; where i and j denote individuals in the sample with $i \neq j$, and t and s denote time periods with $t \neq s$.

Estimation of (4) with a complete panel is straightforward (via fixed effects for example). However, due to incidental truncation, estimation of model (4) in the unbalanced panel requires some caution. It is assumed that w_{it} is observed if the latent variable s_{it}^* crosses the (conventionally) zero threshold[4] while s_{it}^* is explained by a (latent) regression of the form

$$s_{it}^* = \gamma_0 + z_{it}\gamma + \bar{x}_i \mu_2 + \xi_i + \eta_{it}, \tag{5}$$

with

$$s_{it} = 1 \text{ if } s_{it}^* > 0 \text{ (and 0 otherwise)}, \tag{6}$$

where ξ_i is an individual specific effect and z_{it} could be a subset of x_{it}. Letting $\varepsilon_i = (\varepsilon_{i1}, \ldots, \varepsilon_{iT})'$, $\eta_i = (\eta_{i1}, \ldots, \eta_{iT})'$ and ι_T be a $T \times 1$ vector of 1s and where I_T is the identity matrix of order T, it is assumed that the error terms in (4) and (5) are distributed as

[3] For a discussion of issues such as heterogeneity in the slopes of the wage regression and nonlinearities in the wage-schooling profiles see Belzil (2006) and the references therein.
[4] The variable w_{it} will be observed if the wage offer exceeds the individual's reservation wage, w_{it}^r.

$$\begin{pmatrix} \iota_T\alpha_i + \varepsilon_i \\ \iota_T\xi_i + \eta_i \end{pmatrix} \sim N\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma_\varepsilon^2 I_T + \sigma_\alpha^2 \iota\iota' & \sigma_{\varepsilon\eta} I_T + \sigma_{\alpha\xi}\iota_T\iota_T' \\ & \sigma_\eta^2 I_T + \sigma_\xi^2 \iota_T\iota_T' \end{pmatrix}\right), \tag{7}$$

which is independent of x_{jt} for all i, j and t. Furthermore, $\sigma_\eta^2 + \sigma_\xi^2$ is normalised to 1 for identification purposes.

An additional advantage of this procedure is that it allows the inclusion of a lagged dependent variable term in the set of regressors, z_{it}, in the selection equation (5). This enables the distinction of individual effects from the influence of state dependence and ensures that the error components and the correction terms do not incorrectly incorporate the effect of the dynamics attributable to the past state (Vella, 1998). Including a lagged outcome variable term, however, carries the extra cost of having to account for the 'initial conditions'. If the initial conditions of s_{it} could be assumed truly exogenous, the maximum likelihood estimator in the probit equation is consistent and asymptotically efficient (Heckman, 1978, 1981).

Since individuals in the sample have been in the workforce before the start of the sampling process, there is reason to believe that the initial conditions are endogenous and need be accounted for. The procedure suggested by Wooldridge (2005) is followed whereby the joint distribution of $s_i = (s_{i1}, \dots, s_{iT})$ is obtained conditional on (s_{i0}, z_i). To obtain this joint distribution one has to specify a density for the unobserved effect given (s_{i0}, z_i), but since the choice for this density is not restricted by the specification of $f(s_{i1}, \dots, s_{iT}|s_0, \mathbf{z}, \xi; \boldsymbol{\beta})$, one can conveniently choose it to be the normal with $(\mu, \sigma_.^2)$. In practical terms this means that one will have to condition on s_{i0} and z_i in each time period. Therefore the model specified in (5) can be expanded to

$$s_{it}^* = \gamma_0 + \rho s_{it-1} + z_{it}\gamma + \bar{x}_i\mu_2 + \psi s_{i0} + \xi_i + \eta_{it}. \tag{8}$$

Equations (4), (5) or (8), (6) and (7) describe the full model depending whether one includes a dynamic term in the selection equation or not.

Central to the consistent estimation of the model, is the implicit conditioning on the outcome of the selection process. Following Nijman and Verbeek (1992), the conditional expectation of the error terms in (4) given $s_i = (s_{i1}, \dots, s_{iT})'$ will be nonzero if either $\sigma_{\varepsilon\eta} \neq 0$ or $\sigma_{\alpha\xi} \neq 0$ thus the ML or pooled OLS estimators on the balanced panel may be inconsistent due to self selection bias. A solution to the problem is the inclusion of the expectations of the error components α_i and ε_{it} conditional on the selection vector s_i in the model as additional explanatory variables. The remainder of the error term will be independent of the selection vector by construction.

The conditional expectations of the two error components of the error term in (4) can be written as $E(\alpha_i|s_i) = \sigma_{\alpha\xi}A_{1i}$ and $E(\varepsilon_{it}|s_i) = \sigma_{\varepsilon\eta}A_{2it}$, where

$$A_{1i} = \frac{1}{\sigma_\eta^2 + \hat{T}_i \sigma_\xi^2} \sum_{t=1}^{T} l_{it} E(\xi_i + \eta_{it} | s_i)$$

(9)

and

$$A_{2it} = \frac{1}{\sigma_\eta^2} \left[E(\xi_i + \eta_{it} | s_i) - \frac{1}{\sigma_\eta^2 + \hat{T}_i \sigma_\xi^2} \sum_{t=1}^{T} l_{it} E(\xi_i + \eta_{it} | s_i) \right]$$

(10)

where $\hat{T}_i = \sum_{t=1}^{T} l_{it}$ is the number of periods individual i participates in the panel. The conditional expectation of $\xi_i + \eta_{is}$ given s_i is given by Nijman and Verbeek (1992, pp 256-7) as

$$E(\xi_i + \eta_{it} | s_i) = \int_{-\infty}^{+\infty} [\xi_i + E(\eta_{it} | s_i, \xi_i)] f(\xi_i | s_i) d\xi_i.$$

(11)

The conditional expectation of η_{it} given s_i and ξ_i is given by

$$E(\eta_{it} | s_i, \xi_i) = (2s_{it} - 1)\sigma_\eta \frac{\phi\left(\frac{B_{it} + \xi_i}{\sigma_\eta}\right)}{\Phi\left[(2s_{it} - 1)\frac{B_{it} + \xi_i}{\sigma_\eta}\right]},$$

(12)

which follows from the independence of the probit error terms conditional on the unobserved effect. The conditional distribution of the unobserved effect ξ_i is given by

$$f(\xi_i | s_i) = \frac{\prod_{t=1}^{T} \Phi\left[(2s_{it} - 1)\frac{B_{it} + \xi_i}{\sigma_\eta}\right]^{l_{it}} \frac{1}{\sigma_\xi} \phi(\xi / \sigma_\xi)}{\int_{-\infty}^{+\infty} \prod_{t=1}^{T} \Phi\left[(2s_{it} - 1)\frac{B_{it} + \xi_i}{\sigma_\eta}\right]^{l_{it}} \frac{1}{\sigma_\xi} \phi(\xi / \sigma_\xi) d\xi},$$

(13)

where B_{it} is the deterministic component of the first step random effects probit selection equation.

Nijman and Verbeek note that an approximation of the two correction terms, A_{1i} and A_{2it}, can be estimated by replacing the unknown parameters by their respective estimates from the first stage selection model since the conditional expectation $E(\xi_i + \eta_{is} | s_i)$ is a function of the data and the parameters in the selection model only. Conventional t −tests or a standard F or Wald test of the significance of the corresponding coefficients additionally provides a test of non-response bias.

A potential drawback of this procedure is the fact that the evaluation of the conditional expectation in the correction terms requires numerical integration, which makes it less straightforward and more computationally burdensome than in the case of $T = 1$. Once the terms in (9) and (10) have been estimated, the model of interest can be estimated over the subsample for which w_{it} is observed since the correction terms will 'account' for self selection bias.

To summarise the procedure followed here, the first stage involves the estimation of an equation for participation in gainful employment over the entire population. In the dichotomous outcome variable case, the likelihood function has the panel probit form (Vella, 1998) and thus the selection equation is estimable by a random effects panel probit model. After, the reduced form estimates from stage one are used to compute the correction terms A_{1i} and A_{2it}. The primary model of weekly earnings determination is then estimated in the second stage by OLS/GLS with the addition of the correction terms in the set of the regressors.

III The data

The data used in the analysis are taken from the British Household Panel Survey for the period of 1998 to 2005, resulting in individuals being sampled on eight occasions between these dates. Individuals are present in the first wave of observation (1998) and are subsequently allowed to drop out of the sample; once an individual drops out she is not allowed to re-enter the sample. Subjects may not be able to provide valid information on some variables in some instances (waves), a situation referred to as incidental truncation. Self-employed individuals are excluded from the sample, as are those in full time education, retirement and those out of the labour force due to long term sickness and/or disability.

The sample is almost equally divided between males (47.9%) and females (52.1%) of working age at the time of the interview, with the average age being 45.4 and 46.1 respectively. An almost even number of men (38.5%) and women (37.1%) are employed in managerial and technical occupations in the sample. Women dominate skilled non-manual occupations (36.1%) as opposed to 11.2% of males while men outnumber women by almost 3.5 to 1 in manual (skilled) occupations – 26.5% and 8% respectively (Table 1 summarizes). Almost the same is true for professional occupations in the sample, where 9% of men are employed, in contrast to just 3% of women.

[table 1 here]

The average real weekly earnings of individuals in the sample are £456.6 for males and £325.4 for females in full time employment. The corresponding figures for part-time employees are £144.1 for males and £122.1 for females. The difference between real earnings of the two genders is lowest amongst professional occupations and becomes more acute in managerial and technical occupations with the average real weekly earnings of a full-time male employee in the private sector being £592 as opposed to £409 for a female in the same category. This translates to a difference of 31% in the weekly earnings between men and women managers in the private sector with the corresponding figure in the public sector being around 23%. Table 2 presents average real weekly earning for men and women in the private and public sectors by occupational classification.

[table 2 here]

[table 3 here]

Table 3 presents the average hours worked in a week for both men and women in the public and private sectors. Working hours are defined as normal working hours plus usual paid overtime. On average, male and female full-time employees in the sample work for 42.6 and 37.3 hours per week respectively. The corresponding figures for part-time employees are 19.5 and 19.3 hours for men and women respectively.

Table 4 presents estimates of the average real hourly wage for full-time employees. Men in professional occupations, earn around 17.5% more than women per hour on average in the private sector but not in the public sector. Male employees across the occupational grid, in fact, appear to earn more in both sectors with the exception of professional and skilled manual occupations in the public sector where the average hourly real wage appears equated. Women in the public sector appear to earn more per hour on average than their private sector counterparts with the exception of women in unskilled occupations.

[table 4 here]

Training measures

From wave eight (1998) onwards the BHPS expanded the range of questions regarding work-related training activities amongst participants to include information on multiple training spells within the reference year, the location of the training activity, information on the financing and duration of the training spell and on duration and whether training was accredited or not. These complement the existing questions on the spell and purpose of training.

Participants responding positively to the question of training participation are further asked to indicate where the training took place and what the purpose of it was. From the responses in the former question it is possible to construct a proxy variable for on-the-job and off-the-job training as well as a further one recording training undertaken with a previous employer. The latter question (purpose of training) is coded in five non-mutually exclusive categories, namely, the question is coded as "Was this course or training…"

i. To help you get started in your current job

ii. To **increase** your skills in your current job e.g. by learning new technology?

iii. To **improve** your skills in your current job?

iv. To **prepare** you for a job or jobs you might do in the future?

v. To **develop** your skills generally?

and it is used to construct a variable indicating general and specific training. The first three categories (i, ii and iii) are taken to indicate specific training while the last two (iv and v) indicate general training.

The variable recording the source of financing for the training spell also serves the purpose of identifying general and specific training under the assumption that employers will not finance investments in general training. Additionally, the nature of training (general or specific) is determined from whether the training has led to a qualification or not. Training that has led to part or full qualification will almost certainly be regarded as general from both current and potential employers.

The existing BHPS variable recording the financing of the training activity needs to be recoded. The reason for this is that a proportion of the participants who undertook training in the sample, respond that there were no fees associated with their training. This, as already mentioned, may distort the true extent of employer financed training activities if not appropriately accounted for. Specifically it is possible that individuals record no training fees and equate the training costs to zero without considering the costs borne by the employer. This potential problem has also been recognized and highlighted by Booth and Bryan (2002). For the purposes of this study therefore, cases where 'no fees' were reported are incorporated in the 'employer financed' category.

Around 29.6% of participants report undertaking some form of work-related training during the period of observation, 27.9% of men and 31.2% of women. Almost a third (29.7%) of all training reported is characterised as on-the-job training (defined as having taken place in the current or former workplaces). The majority of training is reported as having been financed by the current or future employers, around 82.5%. This figure includes the percentage of training reported as having no training fees associated with while the rest of reported training has been financed either by the individual (14.7%) or some government scheme or other arrangement (2.8%). These figures need to be viewed with some caution; a non-negligible proportion of individuals (30%) in the sample report that there were no fees associated with their training. However, this may be misrepresenting the facts. The portion of individuals reporting that there was no training fee associated with their training course may not be aware that their employer has covered the costs.

Panel (a) of Table 5 presents a break-down of training participation by sector and gender in the sample. Notably, most reported training is financed by the current or previous employer and is thus regarded as general in nature. Private sector employees in the sample engage in less work-related training in comparison to the public sector ones. This may be due to the private sector attracting more able employees who require less training. Women in the public sector report considerably more work-related training than men. However, this may be the result of the composition of the sample with more than twice as many women being employed in the public sector. Very few individuals in the sample choose to engage in any form of work-related training that they have to finance themselves and government sponsored training appears to be balanced between the public and private sectors. Almost half of all the training activities undertaken led to a part or full qualification (e.g. NVQs).

[table 5 here]

Panel (b) of Table 5 presents work-related training occurrence by occupational grouping for men and women in the public and private sectors. Professionals and managers are more likely to engage in work-related training compared to administrators and floor personnel. This is suggestive of the fact that more intricate jobs require both higher and more updated levels of skills. Women in professional and managerial occupations appear to receive more training than men and women across the occupational groups appear to train more in the public sector – this may, however, be a feature of the data, females dominate the public sector in terms of numbers employed with men in managerial and administrative jobs accounting for just over a third of all employees in these groups in the sample.

The dependent variable is (the natural logarithm of) real weekly earnings[5] constructed from the derived variable recording annual labour income in the BHPS[6]. The measure is exact i.e. annual income is divided by fifty two to produce the weekly earnings. The set of independent regressors is further complemented with demographic and socio-economic variables and individual characteristics.

IV Econometric Estimates

Participation in the workforce is modelled as a random effects probit model and its estimates are presented in Table 6, which also presents estimates from the static selection equation (5) for comparison. According to standard theory, an individual will choose to supply labour when the wage offer exceeds her reservation wage. The labour supply decision in this context is specified as a function of personal attributes, job/employer characteristics and past state. The latter is found to have a strong and statistically significant impact on current behaviour and thus is interpreted as one of the major determinants of labour supply. In other words, state dependence effects are quite significant in the labour supply decision. The coefficient of the term capturing the effect of the initial conditions is found to be highly significant suggesting that initial conditions are not in fact exogenous and should be controlled for.

The coefficient on the variable recording the state of health of the individual is found to be significant suggesting that good health is one of the determinants of labour supply, which makes intuitive sense. Being married also increases one's likelihood of being in gainful employment possibly reflecting the increased responsibility that comes with being in partnership and/or the provision requirements for the family.

Higher educational qualifications in the selection equation are found not to have a significant impact statistically. The coefficients of the regional dummies[7] for the South (west and east) and the Midlands are positive and statistically significant, picking up local labour market conditions in those regions.

[5] Earnings are deflated using the RPI and expressed in constant 2005 prices.
[6] This is a measure of income based on actual hours worked including paid overtime. End-of-year bonuses and other extraordinary payments received in the year are included.
[7] Not reported in table 7.6 but available upon request.

The selection equation serves as a stepping stone to the primary model of interest, the wage equation. Nonetheless, it provides some interesting results in this dynamic specification; most notably, the resulting state dependence effect in the individual's decision to engage in gainful employment or not.

[table 6 here]

The earnings equation is estimated within a random effects specification following the procedure adopted in Nijman and Verbeek (1992) and described in section II. Under random effects estimation, the unobserved element responsible for selectivity bias cannot be removed following a data transformation as with fixed effects estimation. Consistent estimation requires that potential selectivity be controlled for by some proxies of the unobserved components in the primary equation. As noted previously, the conditional expectations of the two error components of (14) are a function of the data and parameters of the selection equation only; therefore, even though (9) and (10) are not observed, they can be consistently estimated if the unknown parameters are replaced by their estimates from the random effects panel probit model of selection. The resulting 'correction' terms are added as regressors in (14), which is then estimated over the subsample for which $s_i = 1$, i.e. $w_{it}$is observed, as these two terms account for the selection bias (Vella, 1998). A conventional test of significance of these two coefficients is a test for attrition bias.

The evaluation of the conditional expectations in these correction terms requires numerical integration since the integral in the denominator of (13) has no closed-form solution. This feature makes this two-step procedure more computationally demanding than in the single wave case and less attractive than standard fixed effects methods.

A generalized least squares procedure is used to obtain consistent estimates of the parameters of interest with valid standard errors under the null hypothesis $\sigma_{\varepsilon\eta} = \sigma_{\alpha\xi} = 0$. If this hypothesis holds, and if the unobserved determinants of participation in employment are uncorrelated with the unobserved determinants of wages, missing observations in the sample are missing at random and no selectivity bias occurs in the wage equation.

Identification requires that the matrix of first derivatives of the variables in the deterministic part of both the selection and primary equations has full column rank, in which case the parameters of interest are identified from non-linearities in either equation or from a non-linear mapping from the variables in the selection equation to the correction terms. Vella and Verbeek (1999) argue that in models where there are missing observations for the dependent variable of interest but the endogenous selection variable is fully observed, as is the case here, there are not any non-linearities in the correction terms. The authors further note that identification in such models is achieved from non-linearities in either the participation or wage equations, otherwise, exclusion restrictions are required in the wage equation (one for each endogenous variable).

The results from the GLS procedure are reported in column 1 of Table 7 and can be used to obtain a test of selection bias using either conventional t −-tests or a Wald test for the statistical significance of the correction terms. Table 7 also reports OLS estimates with and without the correction terms and Fixed Effects estimates in columns 2, 3 and 4 respectively for comparison.

[table 7 here]

The GLS estimates are used to test for non-response bias using a Wald test on the significance of the two correction terms, which gives the insignificant value of 1.34. Clearly the hypothesis of no attrition bias is not rejected. This may also be reinforced by the relatively small differences in the results obtained from estimating the model without the inclusion of the correction terms.

The reported intercept from the fixed effects estimator is the average value of the fixed effects. When estimating (14) via fixed effects, the parameters β_0 and α_i do not have a unique solution thus a constraint on the system needs be imposed before estimation can proceed. The constraint imposed here is $\sum_{i=1}^{N} \alpha_i = 0$.

The main training measure included in the primary earnings equation is general training as derived from the reported purpose of the training spell[8]. The estimated coefficient is negative and statistically significant (even though at a low level of significance) indicating that general training is in fact financed by the individual through lower wages. This result is consistent across estimators with the exception of the fixed effects model. The magnitude of the coefficient from the OLS regressions is slightly higher than the one from GLS. This finding provides support for the conclusions of the orthodox human capital theory with regards to training sponsorship by the firm.

A number of specifications have been investigated with alternate training measures, namely, general and specific training (indicated by whether the training undertaken was accredited or not respectively and as derived from the way reported training is financed), on-the-job training (derived from the variable recording the location training was undertaken) and training with a previous employer (again inferred from the location where training was undertaken). The estimated coefficients for each of these measures are reported in the second panel of table 7; all equations include a set of regressors identical to the ones used for the reported equation. Differences in the magnitude of the estimated coefficients in the equations for different training measures are negligible and thus reporting is withheld for brevity (the full set of estimates is available from the author upon request).

Certified training is found to have a negative and significant effect (except in the fixed effects equation again) thereby supporting the claim that employers will not sponsor investments in general human capital. Specific training appears to have a positive and statistically significant effect on real weekly earnings of employees, as postulated by competitive theory. This result is not consistent across all estimators used but only when OLS with or without the added correction terms is used.

Training with a previous employer appears to have a negative but statistically insignificant impact on employees' weekly earnings indicating that human capital investment undertaken with a previous

[8] A specification with a broad measure of training (namely, if any form of work-related training had been undertaken in the 12 months prior to the interview) was also considered but the estimated effect of training was found to be insignificant.

employer is necessarily specific and thus is not of value to the current employer i.e. the individual's marginal productivity with the current employer is not raised as a result of previous specific training – training with a past employer is not transferable. Again, this result is in line with standard theory.

On-the-job training appears to have a negative impact on weekly real earnings. The estimated coefficient is statistically significant only when OLS estimation without including the correction terms is applied (or OLS with corrections but at a lower significance level). The result of a negative effect of on-the-job training may be due to the nature of on-the-job training provided as primarily 'induction' training. In such circumstances, individuals may initially experience lower wages until they become familiar with the specific internal processes in operation in the firm and thus more productive.

Age enters the wage equation both in levels and in quadratic form[9] with both terms having a significant effect on earnings (apart from the quadratic term in fixed effects estimation). The model was specified with a variable measuring job tenure as well. When both terms were included the effects were small and insignificant. When only tenure was included in the model (levels and quadratic form) it had the same effect as age.

Experience, in deviation from the prototypical Mincerian equation (Mincer, 1958, 1962, 1970, 1974), is not included in the primary specification. It is somewhat problematic to construct an accurate variable for the individual's experience from existing data. The BHPS records the age the individual left further education but that does not preclude her return into full time education at any point prior to the start of the sampling process. An accurate measure of experience may therefore be possible to construct for some respondents but not all. Nonetheless, an equation including a variable recording potential labour market experience under the assumption that individuals do not take breaks from the workforce after leaving full time education for the first time (and a quadratic term), has been estimated and reported insignificant effects and little impact on the significance and magnitude of the remaining regressors.

The presence of children under the age of 12 in the household also has a positive and significant impact on weekly earnings. This estimate may pose as somewhat counterintuitive since an *a priori* expectation would be the presence of young children to restrict parents' supply of labour resulting in lower earnings. One plausible explanation is that recent working-time directives allow parents to take advantage of flexible working hours schemes such as job sharing and working from home, which could result in parents supplying the same (or even more) hours as pre child rearing. Furthermore, parents of young children are faced with added expenses and hence may need to supply more hours of labour. Not surprisingly, being employed in a managerial position increases one's earnings substantially as suggested by the relatively large coefficients on the variables recording managerial and supervisory positions.

[9] Human capital theory suggests that age, as a proxy for labour market experience, has a positive, non-linear effect on earnings. When, however, individuals do not have a continuous labour supply profile over their working lives i.e. they experience interruptions in employment (as is likely for women due to family commitments and/or child bearing for example), age may not be a well specified proxy for the effect of labour market experience on earnings (Stratton, 1995).

Changing employers appears to reduce average weekly earnings. This may be indicative of the non-transferability of training – current employers do not compensate for investments with previous employers. This estimate suggests a considerable pay cut for people moving jobs, which would discourage labour turnover but it may also be picking up involuntary job transitions. Moreover, it may be driven by individuals seeking career changes. Such individuals are likely to expect and accept considerable pay cuts. Complete individuals' work histories are not possible to be constructed from available data and hence the latter remains a hypothesis. However, caution need be exercised in the case of this variable since it records change of employer or promotion. Unfortunately it is not possible from existing information to distinguish between the two.

Earnings also appear to significantly increase depending on the size of the employing organization with larger (in terms of manpower) firms offering higher wages. This finding is not surprising and could be the result of either larger firms paying better in general or due to the fact that they are able to attract more highly qualified and skilled individuals who will accordingly be compensated with higher wages. An alternate explanation could also be presented in terms of economies of scale in human capital investments; larger firms can benefit from reduced costs of training given their size, combined with the fact that they inherently provide higher job security due to size (or at least be perceived by workers to do so), individuals are more committed to the firm, which in turn makes human capital investment in them (in specific skills) more profitable in light of the extended time horizon in which it can be amortized. This additional specific (and accumulated) human capital of the individuals is subsequently reflected in their wages.

Clifton (1997) argues that employer (work environment) characteristics may promote motivation and effort in the organizational setting. Therefore the positive impact on earnings of such employer characteristics as size of the firm may also act indirectly through the unobserved components. Other employer characteristics such as location and economic sector are controlled for by including appropriate arguments in the estimated equations.

The educational attainments of the workers naturally have a considerable impact on their wages. Educational qualifications acting either as a proxy of inherent ability or for acquired human capital, play a significant role in the determination of the wage offer to the individual. The higher qualification an individual possesses, the higher her weekly earnings are. A first or higher degree appears to have the most significant impact on weekly earnings followed by more vocational qualifications such as teaching and/or nursing certificates.

The coverage of the workplace by a trade union increases the earnings of workers; this result follows almost intuitively from the (partial) purpose and role of the TU, which is to advance the living standards of its members through higher wages and increased job security. Trade Unions push for higher wages for their members during the bargaining process and through increased job security translated in less staff turnover and a subsequent increase in the accumulation of firm-specific human capital, firms are more inclined to offer higher compensations.

Training and Earnings between groups

The impact of training on weekly earnings is further examined for different groups of employees. This allows an assessment of potential differences in the effect of training between employees with different characteristics. The previous results suggest that there exist differences in the weekly earnings between men and women. Estimating separate wage equations for either gender provides a 'clear' measure of the impact of training on earnings.

Furthermore, it has been well established in the literature of the determinants of training that employees in higher occupational ranks engage in more work-related training (Blundell *et al*, 1999). Professional and managerial positions require employees to perform more intricate tasks and consequently higher ability employees will be assigned such tasks. It has also been documented that higher ability employees are more profitable to invest in since they should generate higher rates of return from human capital investments (Bishop, 1997). In the sample used here, 33.5% of white collar workers report some form of work-related training in the observation period as opposed to 21.5% of their blue collar counterparts. To explore the differences, if any, in the impact of training between these groups of employees, earnings equations are estimated for each subsample. Table 8 presents GLS estimates for each group.

The results from the regressions for male and female employees fail to report any significant effect of general (as defined here) training on earnings. The reported coefficients have nonetheless the 'correct' sign in accordance with standard theory. The negative coefficients indicate the reluctance of employers to finance general training. A negative and insignificant impact of general training on earnings is also found for white and blue collar employees. General training, as proxied by whether the training was accredited or not, has a negative and statistically significant effect on the earnings of male employees and white collar workers but the estimated coefficients for female and blue collar employees are statistically insignificant.

[table 8 here]

Employer financed training has an insignificant effect on average weekly earnings across groups of employees. The effect of training with a past employer is insignificant across both genders and groups, same as on-the-job training. The partial effects of the rest of the regressors remain largely unaltered.

Further to estimating separate earnings' equations for different groups of employees, interaction variables have also been used to assess the impact of training across subsamples. For the general definitions of training used, gender interactions were statistically significant, whereas interactions with the two skills groups were not (unless at a very low level of significance). For the definition of specific training, gender interactions were statistically significant, as were for blue collar employees (negative). For on-the-job training both gender and skills group interactions were found statistically significant. These results legitimise the break down of the sample to different subgroups.

The results presented here are largely in line with other findings in the literature. Almeida-Santos and Mumford (2006) using four waves of the BHPS (1998-2001) investigate the effects of training on wages in Britain and find small yet statistically significant effects for a variety of training measures. They employ fixed effects/instrumental variables estimation to account for heterogeneity in their panel whereas this study explicitly models selection into the sample; they use fewer periods and different (broader in the case of general training) definitions of training measures which may explain the differences in the estimated effects. In addition, the employed sample in the Almeida-Santos and Mumford study includes self-employed individuals between the ages of 18 to 65, whereas I have restricted the sample to employees only between the ages of 16 to 65. Moreover, Almeida-Santos and Mumford in their study decompose their sample into distinct age bands and find significant gains from training only for workers above the age of thirty. Given that such disaggregation was not applied in this study may explain some of the differing estimated effects. Booth and Bryan (2006) and Melero (2004) also use the BHPS to estimate wage returns to training. The definitions of training used in these studies together with the different approaches to modelling (specification of the wage equation) and the composition of the sample could account for the higher magnitude coefficients obtained by Booth and Bryan (2006) for the period of 1998 to 2000 and Melero (2004) for the period 1991 to 2002.

V Conclusion

The impact of formal human capital investments on wages has been well-documented in the literature. The effects of work-related training on wages, however, have received considerably less attention. Early attempts involved estimation of Mincer-type wage equations either on a single cross section or on a small panel using fixed effects estimation techniques to rid the estimates of possible selectivity biases induced by the endogeneity of the training decision. The development of richer dataset and extended panels allows for different estimation techniques such as random effects to be used so as to provide more and better quality information on the event, type and duration of work-related training occurrences.

As mentioned, selectivity bias needs be accounted for in any study investigating the effects of training on wages. The decision to participate in work-related training may be influenced by unobservable, to the analyst, factors, which may in turn affect wages. Such factors include motivation, inherent ability and effort. The treatment of self-selection, as it has come to be referred to, in cross sectional studies is, nowadays, straightforward and involves estimation of the primary wage equation of interest with the inverse Mill's ratio from a first-step reduced form model of participation as additional regressor. This procedure was developed by Heckman (1979) and has, and still is, widely applied.

With panel data, accounting for self-selection bias is even easier, provided the primary equation of interest is estimated in a fixed effects environment. The within transformation applied in the data in this context, guarantees the elimination of any influences from the unobserved effects by removing them from the data. This procedure will result in consistent estimates under the assumption that the correlation between the unobserved components influencing participation and the outcome of interest operates only through time invariant elements.

Nijman and Verbeek (1992) adopted a different estimation technique, which is an extension of the Heckman (1979) procedure to the panel data case. This method involves the estimation of the primary equation of interest in a random effects environment with the inclusion of estimates of the conditional expectations of the two error components for the primary equation as additional regressors. These conditional expectations act as correction terms and their estimates can be obtained from a first-step reduced form participation equation since they are functions of the data and estimated parameters only.

In this study the effects of different types of work-related training on the earnings of British employees is investigated using the procedure suggested by Nijman and Verbeek (1992). Data from the BHPS for the year 1998 to 2005 on employees is used. In the first step, a random effects panel probit model for participation into gainful employment is specified and in the second step, a Mincer-type earnings equation is estimated.

From the first-step participation equation, it is concluded that state dependence is a major determinant in the probability of supplying labour. Other significant determinants include the level of schooling and educational attainment, the size of the organization and occupational status.

The results from the regressions provide support for the standard human capital theory, which postulates that employees will finance general training themselves through lower wages, by reporting a reduction in weekly earnings for those who engage in general training. The effect of general training on men and women is almost identical.

The positive effect of specific training, again in line with neo-classical theory, is greater for blue collar workers suggesting that they realize higher productivity gains compared to their white collar counterparts. Similar results are obtained from alternative measures of general and specific training, namely, accredited training, employer financed training and on-the-job training.

The results also suggest that most training is specific and non-transferable across employers. Employees who change employers/jobs face reduced earnings in comparison to when they continue their relationship with the firm.

Selectivity appears not to be a problem in the estimated models with individual and joint significance tests of the coefficients of the two correction terms failing to reject the respective null hypotheses. An exception is the subsample of men in the earnings growth equation suggesting that for these workers unobserved effects influencing their participation into employment decision are correlated with unobserved effects affecting their productivity. The rest of the results are in line with previous research in the area.

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Table 1 Occupational classification of sample participants

	Males		**Females**	
	Freq.	%	Freq.	%
professional occupations	885	9.02	330	3.09
managerial & technical occupations	3,783	38.57	3,966	37.15
skilled non-manual occupations	1,101	11.23	3,860	36.16
skilled manual occupations	2,606	26.57	860	8.06
partly skilled occupations	1,223	12.47	1,235	11.57
unskilled occupations	209	2.13	425	3.98
Total	9,807	100	10,676	100
Private Sector	Freq.	%	Freq.	%
professional occupations	622	8.19	113	1.94
managerial & technical occupations	2,808	36.95	1,521	26.06
skilled non-manual occupations	657	8.65	2,728	46.74
skilled manual occupations	2,381	31.33	539	9.23
partly skilled occupations	959	12.62	728	12.47
unskilled occupations	172	2.26	208	3.56
Total	7,599	100	5,837	100
Public sector	Freq.	%	Freq.	%
professional occupations	263	11.91	217	4.48
managerial & technical occupations	975	44.16	2,445	50.53
skilled non-manual occupations	444	20.11	1,132	23.39
skilled manual occupations	225	10.19	321	6.63
partly skilled occupations	264	11.96	507	10.48

unskilled occupations	37	1.68	217	4.48
Total	2,208	100	4,839	100

Table 2 Av. Real Weekly Earnings of FT employees by occupation (£) in 2005 prices

	Private Sector		Public Sector	
	Males	**Females**	**Males**	**Females**
professional occupations	565.0	539.9	577.2	503.1
managerial & technical occupations	592.4	409.9	543.2	422.6
skilled non-manual occupations	361.0	239.8	444.9	275.9
skilled manual occupations	361.6	230.7	336.5	240.7
partly skilled occupations	282.7	172.1	309.2	216.5
unskilled occupations	261.0	188.1	242.7	185.3

Table 3 Av. Weekly Working Hours of FT employees (Normal hours + Usual Paid OT)

	Private Sector		Public Sector	
	Males	**Females**	**Males**	**Females**
professional occupations	39.4	36.9	41.8	37.5
managerial & technical occupations	41.7	38.4	39.7	36.6
skilled non-manual occupations	40.0	36.9	41.0	36.4
skilled manual occupations	45.8	40.6	41.8	36.0
partly skilled occupations	44.5	38.7	44.3	35.7
unskilled occupations	46.1	35.6	39.7	35.4

Table 4 Av. Hourly Real Wage of FT employees by occupation (£) in 2005 prices

	Private Sector		Public Sector	
	Males	**Females**	**Males**	**Females**
professional occupations	20.0	16.5	18.2	18.1
managerial & technical occupations	20.4	14.3	20.8	17.3
skilled non-manual occupations	11.5	8.0	13.2	8.9
skilled manual occupations	12.6	7.4	10.8	10.3
partly skilled occupations	9.7	7.1	11.1	7.6
unskilled occupations	10.6	6.6	8.7	6.4

Table 5a Training Participation (%) of FT employees

	Private Sector		Public Sector	

	Males	Females	Males	Females
Any training	26.4	26.0	35.1	45.2
Of which				
Employer Financed	86.1	82.5	86.0	84.9
Self-Financed	11.7	15.4	10.1	11.8
Government Financed / other	2.2	2.1	3.9	3.3
Accredited	44.6	48.5	41.0	44.9
On-The-Job	31.3	31.2	29.0	28.3

Table 5b Training occurrence (%) of FT employees by occupational group

	Private Sector		Public Sector	
	Males	**Females**	**Males**	**Females**
professional occupations	30.6	44.7	34.6	53.6
managerial & technical occupations	32.2	35.1	40.4	48.7
skilled non-manual occupations	25.4	22.1	40.5	39.4
skilled manual occupations	23.7	19.1	30.4	42.5
partly skilled occupations	15.2	19.1	14.0	36.0
unskilled occupations	18.6	16.2	11.1	19.0

Table 6 Selection Equation Estimates

	Random Effects Probit			
	Equation (7.11)		Equation (7.8)	
Personal Characteristics				
Sex (Female)	-0.0367	(0.45)	-0.0423	(0.47)
Age	0.0956	(3.09)	0.1160	(3.44)
Age ^{2}	-0.0012	(3.42)	-0.0014	(3.73)
Race (white)	0.1285	(0.59)	0.1385	(0.57)
Married	0.2243	(2.66)	0.2331	(2.51)
Children <12 in household	0.1186	(0.99)	0.1438	(1.09)
Health status: Good	0.4238	(3.48)	0.4848	(3.70)
Highest Educational Qualification				
Higher degree	0.4058	(1.20)	0.1622	(0.59)
First degree	-0.0005	(0.00)	0.0531	(0.31)
Teaching qf.	0.2265	(0.81)	0.2786	(0.90)
Other higher qf.	0.0863	(0.67)	0.1227	(0.86)
Nursing qf	0.1841	(0.49)	0.2338	(0.56)
GCE A levels	-0.0679	(0.44)	-0.0195	(0.12)
GCE O levels or equivalent	-0.0333	(0.25)	-0.0082	(0.06)
Commercial qf / No O levels	0.1982	(0.67)	0.2368	(0.73)
CSE Grade 2-5 / Scottish Grd 4-5	-0.1018	(0.43)	-0.1046	(0.40)
Apprenticeship	-0.4801	(1.78)	-0.5325	(1.76)
Other qualifications	-0.3036	(0.88)	-0.3144	(0.80)
Auxiliary Parameters				
Intercept	0.1297	(0.12)	0.5441	(0.48)
s_0	0.1129	(0.59)		
s_{t-1}	0.6373	(4.51)		

$\hat{\sigma}_{\xi}^{2}$	0.1597	0.4540
Log-likelihood	-626.7315	-649.6119
N	2366	2422
NT	13096	13469

Notes: (1) Absolute t values in parentheses; (2) Includes dummy variables for region, period and time means; (3) Estimation was carried out in stata © 9.2

Table 7 Earnings Equation under different estimators

	GLS		**OLS** (with corr.)		**OLS** (without corr.)		**Fixed Effects**	
	[1]		[2]		[3]		[4]	
General Training	-0.0055	(0.79)	-0.0259	(2.95)	-0.0270	(3.21)	-0.0003	(0.04)
Personal Characteristics								
Sex (Female)	-0.4251	(25.0)	-0.3246	(34.6)	-0.3223	(35.9)		
Age	0.0576	(11.8)	0.0444	(11.8)	0.0432	(13.5)	0.2661	(1.13)
Age ^{2}	-0.0007	(12.6)	-0.0005	(12.2)	-0.0005	(14.2)	-0.0008	(13.4)
Race (white)	0.0690	(1.44)	0.0483	(1.98)	0.0764	(3.20)		
Married	0.0147	(1.20)	0.0457	(4.75)	0.0423	(4.58)	-0.0029	(0.21)
Children <12 in household	0.0623	(4.07)	0.0137	(1.07)	0.0124	(1.00)	0.0983	(5.84)
Health status: Good	0.0328	(2.27)	0.0802	(4.53)	0.0755	(4.44)	0.0316	(2.23)
Educational Qualification								
Higher degree	0.5466	(11.6)	0.4113	(14.8)	0.4284	(17.5)	-0.0013	(0.01)
First degree	0.4351	(14.5)	0.3865	(21.0)	0.3697	(21.3)	-0.0169	(0.32)
Teaching qf.	0.4399	(8.90)	0.3190	(11.8)	0.3151	(12.7)	0.4145	(3.22)
Other higher qf.	0.1654	(7.19)	0.1694	(11.5)	0.1570	(11.3)	-0.0410	(1.17)
Nursing qf	0.1461	(2.44)	0.1408	(3.75)	0.1035	(2.95)	-0.1519	(1.75)
GCE A levels	0.1611	(5.80)	0.1343	(7.78)	0.1141	(6.99)	-0.0176	(0.42)
GCE O levels or equivalent	0.1377	(5.57)	0.1229	(8.08)	0.1058	(7.32)	0.0013	(0.03)
Commercial qf / No O levels	0.1309	(2.86)	0.0626	(2.41)	0.0563	(2.19)	0.1556	(2.01)
CSE Grade 2-5 / Scottish Grd 4-5	0.0995	(2.53)	0.0823	(3.42)	0.0624	(2.66)	0.0005	(0.01)
Apprenticeship	0.1042	(1.28)	0.0460	(0.97)	0.1291	(3.15)	-0.1532	(1.40)
Other qualifications	-0.0189	(0.25)	-0.2052	(3.74)	-0.1993	(3.95)	0.1440	(1.30)
Job/Employer Characteristics								
Changed jobs	-0.2143	(30.3)	-0.2192	(23.5)	-0.2177	(24.3)	-0.2166	(32.1)
Private Sector	0.0417	(3.30)	0.0199	(2.05)	0.0241	(2.55)	0.0882	(5.91)
Non Permanent position	-0.0838	(4.08)	-0.1098	(4.42)	-0.1348	(6.03)	-0.0801	(4.18)
Part time job	-0.5183	(40.6)	-0.7547	(64.5)	-0.7473	(67.5)	-0.3956	(30.0)
TU coverage in the workplace	0.0695	(6.99)	0.0676	(7.30)	0.0680	(7.65)	0.0592	(5.72)
Managerial position	0.1359	(11.8)	0.2280	(19.7)	0.2426	(22.0)	0.0719	(6.20)
Supervisor/foreman	0.0782	(7.83)	0.0836	(7.60)	0.0872	(8.18)	0.0537	(5.44)
Size of Emp. Org. (Manpower)								
More than 25 / 50 to 99	0.0485	(4.46)	0.1068	(9.02)	0.1120	(9.89)	0.0295	(2.76)

(small)								
100 to 499 (medium)	0.0811	(8.00)	0.1412	(14.6)	0.1391	(14.9)	0.0404	(3.89)
500 or more (large)	0.1138	(9.62)	0.1666	(15.4)	0.1602	(15.4)	0.0552	(4.45)
Auxiliary Parameters								
Intercept	3.2288	(24.2)	3.5183	(30.0)	3.5751	(34.0)	0.7357	(0.28)
$\hat{\sigma}_{\alpha\xi}$	0.0000	(0.17)	0.0000	(0.32)				
$\hat{\sigma}_{\varepsilon\eta}$	0.0000	(0.02)	0.0000	(0.61)				
NT	13778		13778		15515		15515	
Alternate Forms of Training								
Accredited training	-0.0469	(4.04)	-0.0801	(5.99)	-0.0915	(7.05)	-0.0096	(0.79)
Employer Financed Training	0.0074	(1.07)	0.0260	(3.00)	0.0313	(3.77)	0.0029	(0.43)
Training with Previous Employer	-0.0176	(0.32)	-0.0734	(1.11)	-0.0724	(1.11)	-0.0146	(0.26)
On-the-Job Training	-0.0051	(0.42)	-0.0195	(1.37)	-0.0311	(2.25)	-0.0077	(0.61)

Notes: (1) Absolute t values in parentheses (for GLS only valid under $\sigma_{\varepsilon\eta} = \sigma_{\alpha\xi} = 0$); (2) All models include dummy variables for region, period and occupational classification and time means; (3) The models for the alternate training measures include regressors as specified for the equation for general training. Tables of full results are presented in the Appendix to this chapter; (4) Estimation was carried out in stata © 9.2.

Table 8 GLS estimates of the Earnings Equation for different groups of Employees

	Males		**Females**		**White collar workers**		**Blue collar workers**	
	[1]		[2]		[3]		[4]	
General Training	-0.0000	(0.01)	-0.0078	(0.70)	-0.00795	(0.97)	-0.01046	(0.81)
Personal Characteristics								
Sex (Female)					-0.39386	(19.2)	-0.53609	(18.1)
Age	0.06642	(11.5)	0.04792	(6.31)	0.06484	(10.7)	0.03931	(5.07)
Age ^{2}	-0.0007	(11.4)	-0.0006	(7.32)	-0.00075	(10.9)	-0.00050	(5.77)
Race (white)	0.16065	(2.70)	-0.0204	(0.28)	0.06920	(1.21)	0.13218	(1.58)
Married	0.05781	(3.95)	-0.0279	(1.49)	0.03025	(2.02)	-0.01574	(0.80)
Children <12 in household	-0.1291	(2.04)	0.07817	(4.29)	0.06251	(3.54)	0.10154	(3.40)
Health status: Good	0.04342	(2.40)	0.02889	(1.34)	0.02223	(1.20)	0.04141	(1.93)
Educational Qualification								
Higher degree	0.49863	(8.77)	0.54688	(7.63)	0.53213	(9.59)	1.03072	(3.27)
First degree	0.42555	(11.6)	0.43349	(9.55)	0.45482	(10.9)	0.22783	(3.28)
Teaching qf.	0.11361	(1.36)	0.52535	(8.34)	0.46434	(7.93)	-0.09525	(0.67)
Other higher qf.	0.15683	(5.56)	0.15243	(4.35)	0.20179	(5.45)	0.08009	(2.76)
Nursing qf	0.18309	(0.81)	0.11784	(1.66)	0.18680	(2.73)	-0.13316	(0.75)
GCE A levels	0.20017	(5.93)	0.10242	(2.40)	0.17976	(4.37)	0.09068	(2.30)
GCE O levels or equivalent	0.14662	(4.55)	0.12409	(3.47)	0.15537	(4.00)	0.08502	(2.67)
Commercial qf / No O levels	0.02869	(0.16)	0.14285	(2.64)	0.09008	(1.58)	0.24503	(2.79)

CSE Grade 2-5 / Scottish Grd 4-5	0.13226	(3.02)	0.02545	(0.37)	0.09656	(1.49)	0.06003	(1.27)
Apprenticeship	0.06849	(0.92)	0.05652	(0.19)	0.12293	(0.91)	0.05494	(0.55)
Other qualifications	0.03799	(0.41)	-0.1402	(1.21)	-0.36617	(2.81)	0.17760	(1.96)
Job/Employer Characteristics								
Changed jobs	-0.1717	(21.3)	-0.2544	(22.2)	-0.20142	(24.4)	-0.23831	(18.0)
Private Sector	0.09847	(5.80)	0.00788	(0.43)	0.02349	(1.50)	0.05923	(2.69)
Non Permanent position	-0.0654	(2.25)	-0.0857	(2.98)	-0.10284	(4.08)	-0.05621	(1.65)
Part time job	-0.5524	(17.2)	-0.5100	(32.8)	-0.49794	(33.1)	-0.50731	(21.0)
TU coverage in the workplace	0.06200	(5.60)	0.08009	(4.87)	0.02725	(2.15)	0.15179	(9.68)
Managerial position	0.11432	(8.55)	0.16094	(8.83)	0.13993	(11.3)	-0.01172	(0.23)
Supervisor/foreman	0.05918	(5.04)	0.09398	(5.97)	0.08295	(6.89)	0.05243	(2.92)
Size of Emp. Org. (Manpower)								
More than 25 / 50 to 99 (small)	0.03112	(2.52)	0.06942	(3.94)	0.03500	(2.53)	0.05030	(3.02)
100 to 499 (medium)	0.03996	(3.48)	0.12758	(7.72)	0.08125	(6.54)	0.05152	(3.04)
500 or more (large)	0.09179	(6.82)	0.13449	(7.00)	0.11935	(8.46)	0.06203	(2.93)
Auxiliary Parameters								
Intercept	-36.434	(1.12)	-148.68	(3.22)	-106.49	(3.05)	-80.16	(1.74)
$\hat{\sigma}_{\alpha\xi}$	0.00000	(0.46)	0.00000	(0.17)	0.00000	(0.34)	0.00000	(0.89)
$\hat{\sigma}_{\varepsilon\eta}$	0.00000	(1.52)	0.00000	(1.39)	0.00000	(0.44)	0.00000	(1.60)
NT	6696		7082		9387		4391	
Alternate Forms of Training								
Accredited training	-0.0474	(3.36)	-0.0349	(2.00)	-0.0555	(4.22)	-0.0067	(0.27)
Employer Financed Training	-0.0010	(0.12)	0.0109	(0.99)	0.0101	(1.25)	0.0119	(0.96)
Training with Previous Employer	0.0502	(0.70)	-0.0402	(0.52)	-0.0016	(0.03)	-0.0762	(0.59)
On-the-Job Training	-0.0067	(0.46)	-0.0045	(0.24)	0.0144	(1.02)	-0.0391	(1.62)

Notes: (1) Absolute t values in parentheses (for GLS only valid under $\sigma_{\varepsilon\eta} = \sigma_{\alpha\xi} = 0$); (2) All models include dummy variables for region, period and occupational classification and time means; (3) The models for the alternate training measures include regressors as specified for the equation for general training; (4) Estimation was carried out in stata © 9.2.