THE RELATIONSHIP BETWEEN TRAINING AND EMPLOYMENT GROWTH IN SMALL AND MEDIUM-SIZED ENTERPRISES

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Abstract

This paper provides a rigorous analysis of the impact of training upon the employment growth characteristics of small and medium sized firms. Using appropriate statistical techniques to cope with sample selection biases and heterogenerous employment growth patterns it reveals that training is positively related to employment growth, in particular when it is embedded in a wider range of human relations practices.

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The Relationship between Training and Employment Growth in Small and Medium-sized Enterprises

1 Introduction

This paper examines the impact of training on firm employment growth for a panel sample of UK SMEs. Using a single binary indicator measuring firm training in 1991, Cosh, Duncan, and Hughes (1998) have previously examined the relationship between investment in training and small firm growth and survival. They found a significant impact of training upon performance for the period 1987-90, but an insignificant effect for 1990-95. The principal limitations of this study are both the binary nature of the training variable and that this indicator is observed only for a single time period, together with the assumptions which are necessary to account for the effects of endogeneity. In addition, the authors were restricted to a dataset which prevented them from being able to differentiate between firms based upon the *amount* of funds devoted to training and the extent to which training is a *persistent* activity.

In this study we conduct an empirical evaluation of the different methodologies outlined in Hughes and Weeks (1999) utilising an updated version of the CBR SME Dataset which contains a panel of 760 firms with cross-section data for 1991, 1993, 1995 and 1997, with training measured both in 1991 and 1997. The addition of 1997 survey data is important for a number of reasons. First, the 1991 survey took place in the middle of an economic downturn with a combination of falling GDP and inflation and rising unemployment. In contrast the 1997 survey was conducted amidst very different macroeconomic conditions, with expanding GDP and falling unemployment (see Cosh and Hughes (1998)). Subsequently, despite the lack of a continuous time series, the addition of a data point characterised by a very different set of macroeconomic indicators will allow us to examine the combined effect of these factors on our findings. Second, in 1997 the survey data contains additional information (beyond a binary indicator of whether firms train) in the form of: i) interval level data on training expenditures as a percentage of total sales; and ii) data based upon a number of questions designed to impart information on human resource management including the use of quality circles, labour turnover, job rotation and multi-skilling. With regards to i) the availability of data which provides some indicator of the *intensity* of training will hopefully facilitate greater discrimination in isolating the determinants of training. Existing models based upon binary data suffer from the problem of measurement error because although we observe (quasi) continuous measures on the *causes* of training, the inter-firm variation in the amount of training is lost.[1] For example, it is possible that the finding of an insignificant effect of training on firm performance for the period 1990-95 was due, in part, to the discrete nature of the training measure.

A key objective of this study is to examine the relative gain of utilising alternative measures of training activity on firm employment growth. We first do this within the confines of a two-period model of employment growth and utilise the earlier work of Cosh, Duncan, and Hughes (1997) and Hughes and Weeks (1999) as a point of departure. In future work we intend to examine a number of alternative specifications.

2 Employment Growth and Training: Some Simple Models

To translate this problem into the context of the effects of training on firm employment growth, we first consider a simple abstract model of timing, persistence and the effects of training. We do this by considering a number of firm types which are defined using two binary random variables: whether or not a firm trains, and whether or not a firm survives the observation window. We then compare this representation of the data generating process with the data observed by the analyst.

1. Firm $i \in \Omega$ began training in period t_* and survives at least until period t_2. Throughout the period $t_* - t_2$ training may be either persistent or periodic. Firm $i' \in \Omega'$ survives at least until period t_2 but does not train. We let $\mathfrak{M} = \Omega \cup \Omega'$ denote the sample of surviving firms.

2. Firm $j \in \Theta$ began training in period t_* and fails in period $t_1 < t_2$. Throughout the period $t_* - t_1$ training is persistent or periodic. Firm $j' \in \Theta'$ also fails in period $t_1 < t_2$ but does not train. We let $\zeta = \Theta \cup \Theta'$ denote the sample of firms which fail prior to t_2.

[1] In pure statistical terms models which incorporate data on *both* a discrete indicator such as training and conditional upon training, some measure of the level, produce parameter estimates with higher efficiency.

3. Selection into training for firms i and j may be either i) random or systematically determined by ii) observables or iii) unobservables.

4. The total number of firms alive in period t_* is given by $\Lambda = \mathfrak{M} \cup \zeta$; the total alive in period t_2 is $\Omega \cup \Omega'$.

Based upon 1, 2 and 3 we can clearly identify the issues we will need to tackle if we are to isolate a pure effect of training on employment growth. For example, if selection into training is a random process then we can use firms of type i and i' to evaluate the impact of training. To the extent that this process is not random and to the extent that the characteristics of firms which determine employment growth also affect the decision to train, then firms of type i' will not constitute an adequate control sample.

In addition, we need to account for the possible confounding effects of attrition. Since firms enter into our sample only if a performance measure is available in periods t_* *and* t_2, then in the event of either firm deaths or item non-response, the distribution over our performance variable will be truncated. For example, to the extent that training and slow growth are related to firm survival, our estimates of the impact of training and performance will be misleading. If slow growing trainers are more likely to survive than slow growing non-trainers, then by focusing only on surviving firms, the results may be biased against finding a positive relationship between growth and training. If firm survival over a period $t_* - t_2$ is independent of the decisions to train, *and* selection into the training state is random, then it is possible to make reliable inferences on the impact of training on employment growth using samples Ω and Ω'. If either or both of these conditions are violated then appropriate corrections will need to be made.

If we assume that firms of type i represent random draws from a population of firms and that the *permanent component* of firm performance is constant across training and non-training firms, then a consistent estimate of a training effect on performance (say P) is given by

$$E[P_{it_2} - P_{it_1} | D_{it_*}] \tag{1}$$

where D_{it_*} is a binary random variable equal to 1 if the firm engages in training in period t_* and zero otherwise. (1) represents a simple difference in the unconditional means of the performance variable.

To the extent that selection into training is determined by different permanent components of performance (e.g. it is well established that larger firms have a higher propensity to train) then we need to control for these factors in evaluating the marginal impact of training. In this context we might add a vector of covariates, (in addition to the training variable) say $\mathbf{x}_{it}$, to (1) and estimate a simple linear regression specification. To the extent that the process determining D_{it_*} is endogenous to firm performance then we obviously need to make appropriate corrections in order to isolate a pure effect of training. For example if $D_{it_*} = 1$ iff $\zeta_i < \widetilde{P}$ where $\widetilde{P}$ is a threshold value of performance, then a simple estimate of the effect of training which ignores this selection rule would be biased.

The problems encountered in estimating the impact of training on firm performance are, in general, analogous to the evaluation of training programmes on individual earnings. In particular, a critical issue which confronts both types of studies is the need to recognise the exact nature of the data constraints and the question that is being asked. For example, assuming that we wish to determine the impact of training on the performance of firms, we might wish to evaluate

$$E[P'_{it_{21}}|D_{it_*} = 1] - E[P''_{it_{21}}|D_{it_*} = 1], \tag{2}$$

where $P'_{it_{21}} = P_{it_2} - P_{it_1}$ denotes the observed difference in performance for firms that were observed to train in t_* and $P''_{it_{21}}$ is an estimate of the mean outcome that would have been obtained had the *trainers not trained.* The question we need to address is under what circumstances can we use $E(P^*_{it_{21}}|D_{it_*} = 0)$, where $P^*_{it_{21}}$ denotes the mean performance for non-trainers as a proxy for the unobservable $P''_{it_{21}}$. To examine this problem we subtract the mean outcome for non-trainers from the mean outcome of trainers

$$E(P'_{it_{21}}|D_{it_*} = 1, s_{21} = 1) - E(P^*_{it_{21}} \mid D_{it_*} = 0, s_{21} = 1), \tag{3}$$

and label this expression A. We can rewrite A as additive in two terms by adding and subtracting $E(P''_{it_{21}}|D_{it_*} = 1)$ to (3), giving

$$\{\underbrace{E(P'_{it_{21}}|D_{it_*} = 1, s_{21} = 1) - E(P''_{it_{21}}|D_{it_*} = 1, s_{21} = 1)}_{B}\} + \tag{4}$$

$$\{\underbrace{E(P''_{it_{21}}|D_{it_*} = 1, s_{21} = 1) - E(P^*_{it_{21}} \mid D_{it_*} = 0, s_{21} = 1),}_{C}\}.$$

s_{21} is an additional conditioning variable which is equal to 1 if the firm is still alive in period 2. Note that B represents an estimate of what we wish to evaluate - an impact of training based upon subjecting the *same* group of firms to the training and non-training status. Given that we are operating within a non-experimental framework $E(P''_{it_{21}}|D_{it_*} = 1, s_{21} = 1)$ is not observed. The second term C represents a combination of selection and attrition bias caused, respectively, by the fact that non-participants differ from participants in the non-participation state, and non-random firm death. If C is zero then the process of selecting a class of training firms from the total population of firms is random. In cases where term C is not equal to 0, inferences will be misleading. Note that in focussing on selection bias we may recast this discussion in terms of whether or not the decision to train is weakly exogenous in the sense of Engle, Hendry and Richard (1983) from employment growth. Given the form of (3) and (4) we have implicitly imposed exogeneity by writing the *conditional* distribution of employment growth. This is only valid if the marginal distribution of the training variable contains no additional information. More formally, if we let ζ denote the vector of parameters from a model of the determinants of training, then weak exogeneity of training for employment growth follows if $\partial\alpha/\partial\zeta = 0$ where α is the impact of training on employment growth assuming training is exogenous.

In the above we have provided an abstract characterisation of a simple process of training and employment growth. If we now overlay this with the imperfect measurements of data observation, a number of additional problems are encountered.

1. If the effects of training are cumulative, then any impact of training will be due to both the incidence of training and how long the firm has trained. Training is therefore imperfectly measured, since duration of training is not observed. Note that this situation is in contrast to the empirical analysis of the effects of centrally provided training programmes on individual earnings (see for example, Ashenfelter and Card (1985), Bassi (1983) and Heckman and Robb (1985)). In this instance *individuals* undertake training in a given period and return to paid work. In contrast *firms* may train or not train in each period of business life and, in addition, vary the intensity of training programmes.

2. Consider the situation when we observe more than one indicator of training, namely for all firms we observe $D_{it'}$ and $D_{it''}$ where t' is close to t_1 and t'' is close to t_2. In an earlier study of firm performance over the period 1991-95 Cosh, Duncan, and Hughes (1998) found an insignificant effect due to training if training is measured in 1991. The finding of very

different effects according to when selection into training is measured is consistent with a number of earlier studies. For example, Ashenfelter and Card (1985) note that one of the critical influences on the size of the estimated training effects include timing of the decision to participate in training. In the case of centrally provided manpower training programmes, individuals are selected into training based upon earnings relative to a benchmark. The authors find very different training effects, depending upon whether earnings in the year *prior* to training are the appropriate selection rule, or earnings in the training period itself.

3. The impact of training on firm performance will depend upon a number of factors, such as the *level* of training provision as measured, for example, by the proportion of total labour costs allocated by training. In addition it is necessary to consider the impact of training in conjunction with other factors such as human resource management. This view is based upon the notion that there are complementarities between sets of HRM practices so that the whole is more than the sum of the parts. Thus Black and Lynch (1997), in their work on estimating the impact of training on productivity in US establishments, specifically include measures of other HRM practices such as total quality management and employee participation alongside training indicators. In making this argument they cite in support the theoretical models of Milgrom and Roberts (1995) and the empirical approaches of Huselid (1995) and Ichniowski, Shaw, and Prennushi (1995) and the industry specific studies of Arthur (1994), Bailey (1993) and Kelley (1994a), Kelley (1994b). In their 1997 study, Black and Lynch find evidence that the way HRM strategies are implemented does affect productivity outcomes. This suggests that the definition, and collation, of variables relevant to the implementation of training, and the HRM context in which they are set, should be an important component of survey design. Such variables could include the proportion of workers in quality circles, employee participation in decision taking, and flexible job definitions as well as benchmarking and total quality management. These factors may be included as individual variables, or as composite categorical variables derived by factor or cluster analysis. For example, training may have a significant impact on performance if it is associated with other changes in the way in which labour is organised. If the data observed by the analyst are simply a binary indicator of training provision, then the subsequent loss of information will result in a relative

loss of efficiency and potential difficulty in isolating a significant training effect.

3 The Measurement of Training

Empirical studies, whether of the case study, or econometric kind, have used a wide variety of definitions of the training variable. In general we can identify two types, based upon observing either a binary indicator of training provision, or some measure of the extent of training. The critical distinction between the two types of measurement concerns the information content of the different measures. To the extent that there exists considerable variation in the intensity of training, then a binary indicator based upon the presence, or absence, of training will contain significant measurement error. A recent extensive review by Storey and Westhead (1997) reveals that the majority of studies examining the impact of training on firms use a limited dependent, or categorical, variable measure. This is usually based on whether or not training, or a particular type of training (formal/informal, part time/full time, government sponsored, etc.), has taken place; and on whether or not a particular group or groups of employees, or managers were involved. A more limited subset of the literature uses a continuous variable approach based on estimates of the intensity of training provided (e.g. hours per week spent in training, numbers of employees trained or training expenditures), or a combination of both categorical and continuous variables.

The nature of the training costs question is also important in terms of the econometric methodology. For example, in the CBR SME dataset the training costs variable has a probability distribution with a number of mass points. Most significantly we only observe training costs *conditional* upon the decision to undertake some form of training. As a result there is a significant probability mass at zero. In addition the data is also censored for the firms which undertake training and report training cost information. Firms which spend more than 6% of labour costs on training do not provide the actual percentage but simply provide an indicator. In this respect the training cost variable is both left and right censored. For trainers spending the least amount on training we only know that the amount lies within the 0-1% interval, and as such we also have interval level data. Between these two extremes firms can indicate whether they spend between 1 and 5% on training costs. Thus we note that the training costs variable combines censored, interval and point level data, and it is necessary to account for these features in any subsequent modelling exercise.

4 A Two Period Model of Employment Growth and Training

We present a widely used model of employment growth derived from the Law of Proportionate Effect. This essentially hypothesises that firm growth is a random walk, with the best predictor of next period's size being this period's size plus a random variable. We may write this model in an equivalent form with growth measured as the log of the ratio of closing and opening size as the dependent variable, namely

$$\begin{aligned} Y_{it} &= \omega + \mathbf{x}_{it_1}\boldsymbol{\beta} + \alpha_l D_{it_l} + \theta m_{it_1} + \varepsilon_{it} \qquad (5) \\ D_{it_l} &= 1(D^*_{it_l} = \zeta + \mathbf{z}_{it_1}\boldsymbol{\lambda} + v_{it} > 0), \quad t_1 < l = t' \text{ or } t'' < t_2 \qquad (6) \end{aligned}$$

where i and t index, respectively, firms and time. Our data restricts us to measuring training at only two points - at the beginning ($l > t_1$) or end ($l > t_2$) of the growth period. w and ζ are intercept parameters, Y_{it} = log of the ratio of closing (period 2) and opening (period 1) employment size, m_{it_1} is the log of employment in period 1, $\boldsymbol{\beta}$ is a $k_x \times 1$ vector of parameters, $\mathbf{x}_{it_1}$ is a $1 \times k_x$ vector of covariates, α_l is the effect of training in period l on the change in performance measured by the binary indicator D_{it_l}, and $D^*_{it_l}$ is an unobserved propensity to undertake training. $\mathbf{z}_{it_1}$ is a $1 \times k_z$ vector of covariates which influence the decision to undertake training and $\boldsymbol{\lambda}$ is a $k_z \times 1$ vector of parameters. Note that $\mathbf{x}_{it_1}$ and $\mathbf{z}_{it_1}$ may be overlapping vectors, given that factors which determine growth may also influence the decision to train. If the error terms ε_{it} and v_{it_l} are correlated, then the pure effect of training on firm performance will be confounded. For example, if training firms are, on average, fast growing, then an ordinary least squares estimator of α_l in (5) would overestimate the impact of training. In addition, firms with a slump in orders, but with a productive management, may decide to take a long-term view and include a training programme. The key point to emphasise here is that firms may select themselves into training, based upon unobservables that are time variant.

If we take the expectation of (5) with respect to D_{it_l} we may write

$$Y_{it} = \omega + \mathbf{x}_{it_1}\boldsymbol{\beta} + \alpha_l D_{it_l} + \theta m_{it_1} + E(\varepsilon_{it}|D_{it_l}) + \eta_{it_2}, \qquad (7)$$

where η_{it_2} is a zero mean error term. Given that D_{it_l} is an endogenous regressor, the expectation of the error term is both non-zero and *observation dependent*, and as such may be considered an omitted variable. Assuming that $v_{it} \sim N(0, \sigma^2)$ we may write this expectation as

$$E(\varepsilon_{it}|D_{it_l}) = \delta\widehat{\tau}_i, \tag{8}$$

where $\widehat{\tau}_i$, the generalised residuals from a probit model of the binary training indicator can be written as

$$\widehat{\tau}_i = E[v_{it_l}|D_{it_l}] = (D_{it_l} - \widehat{\Phi}_{it_l})\widehat{\phi}_{it_l}(1 - \Phi_{it_l})^{-1}\widehat{\Phi}_{it_l}. \tag{9}$$

$\widehat{\phi}_{it_l}$ and $\widehat{\Phi}_{it_l}$ are, respectively, the probability density function and cumulative distribution function of the normal distribution evaluated at $\widehat{\zeta} + \mathbf{z}_{it_1}\widehat{\boldsymbol{\lambda}}$. Based upon (7) and (8) if we cannot reject the null hypothesis that $\delta = 0$, then ε_{it} and v_{it} are uncorrelated which therefore implies $\partial\alpha_l/\partial\boldsymbol{\lambda} = 0$.

Focussing on simple binary indicators of training provision, we explore two versions of (6). First, we measure training at the beginning of the period, such that $D_{it_l} = D_{it_1}$, and compare this with the result from measuring training at the end of the period where $D_{it_l} = D_{it_2}$.[2] Second, we utilise both measures of training and construct a dummy variable $D_{it_{21}} = D_{it_2} - D_{it_1}$. $D_{it_{21}}$ has four outcomes based on persistent trainers, no trainers and those that train in one period and not the other. Sample frequencies for this variable are presented in Table 2 which also records average employment for each of the four train states. For firms that are alive in both periods, the most prevalent state is occupied by persistent trainers.

Although we refer to firms for which D_{it_1} and D_{it_2} are equal to 1 as *persistent* trainers, given the lack of a complete time series between these two points, it is not possible to discriminate between firms which undertake training in all intervening years, and firms for which training is periodic. However, a test of the null hypothesis that the training decision in 1997 is independent of the same in 1991 is easily rejected,[3] and suggests that there is some form of persistence over time in the provision of formal training.

[2] Note since our other measure of training is recorded in 1997 and the end period is 1995 we make the assumption that firms training in 1997 were also training in 1995.

[3] $\chi^2_{(1)} = 75.3$.

4.1 Intensity of Training

We also consider a variant of the specification given by (5) and (6), given that we have access to a measure of training intensity. If we observe training costs for the sub-sample of trainers, then we may rewrite (6) as

$$D_{it_l} = \mathbf{1}(D^*_{it_l} = \zeta + \mathbf{z}_{it_l}\boldsymbol{\lambda} + v_{it_l} > 0)D^*_{it_l}, \tag{10}$$

where now the latent variable and observed counterpart, $D^*_{it_l}$ and D_{it_l}, are based upon an intensity measure of training. The observational rule in (10) is such that training costs are zero for non-trainers, or a positive continuous quantity for those firms undertaking some form of training. In this respect the estimation of the parameters for (10) will be similar in spirit to the censored regression model. However, the nature of the training costs data is such that we need to account for both censoring at zero and at an upper threshold of 6%, and in addition, for interval level data for costs less than 6 per cent.

Training costs for firms are recorded as:

1. 0 – no training undertaken. Observations $i \in L$ are left-censored.

2. $j < D^*_{it_l} \leq j + 1 \; \forall j = 0, 1, 2, 3, 4, 5$. Training costs lie between j and $(j+1)$% of total labour costs. Observations $i \in I$ are intervals.

3. $D^*_{it_l} \geq 6$. For firms spending more than 6% we only observe an upper censoring indicator, 6. Observations $i \in R$ are right censored.

Based upon the observational rule implied by 1, 2, and 3 the generalised residuals can be estimated using:

$$E(v_{it_l}|D_{it_l}) = -\sigma_v\phi(\delta)(1-\Phi(\delta))^{-1}\mathbf{1}(D^*_{it_l} \leq 0)$$

$$+\sum_{j=0}^{5}\sigma_v\left\{\frac{\phi(j-\delta)-\phi((1+j)-\delta)}{\Phi((1+j)-\delta)-\Phi(j-\delta)}\right.\mathbf{1}(j < D^*_{it_l} < (1+j))$$

$$+ -\sigma_v\frac{\phi(6-\delta)}{1-\Phi(6-\delta)}\mathbf{1}(D^*_{it_l} \geq 6) \tag{11}$$

where $\phi(.)$ and $\Phi(.)$ are, respectively, the standard normal probability density function and cumulative distribution evaluated at $\delta = \boldsymbol{\lambda}'\mathbf{z}_{it_l}/\sigma_v$. Parameters $\boldsymbol{\lambda}$ and σ_v are estimated by maximum likelihood with the log-likelihood function, l, given by

$$\begin{aligned} l \;=\; & \sum_{i \in L} \log \Phi\left(-\delta\right) \\ & + \sum_{i \in R} \log\left[1 - \Phi\left(6 - \delta\right)\right] \\ & + \sum_{i \in I} \log\left[\Phi(j+1) - \delta - \Phi\left(j - \delta\right)\right] \quad \forall j = 0,1,2,3,4,5. \end{aligned} \tag{12}$$

5 Firm Performance, Training and Firm Size: A Descriptive Detour

In this study we have access to both binary measures of training propensity and an indicator of training intensity, namely training costs as a proportion of labour costs. In Table 1 we explore the proposition that the relationship between the impact of training and employment growth is determined, in part, by the date of the training indicator. Using the Wilcoxon rank sum test we test the hypothesis that there is no relationship between employment growth ($\overline{EG}$) over the period 1987-90 and 1990-95 and the incidence of training, namely $H_0 : \overline{EG}^1_{8790} = \overline{EG}^0_{8790}$, and $H_0 : \overline{EG}^1_{9095} = \overline{EG}^0_{9095}$ where the superscript 1 (0) denotes training (non-training) firms. In the two instances where training is measured after the employment growth period we observe a significant (positive) difference between training and non-training firms. However, over the period 1990-1995, where training is measured in 1991, we cannot reject the null hypothesis. Table 2 presents the joint frequencies of the training decisions of firms in 1991 and 1997 and the average employment level in 1995 ($\overline{EMPL}_{95}$) for each training state. We note that the most prevalent state is occupied by firms which were observed to train in both periods, which on average are much larger in terms of employment. Table 3 presents data for training costs.

The first point to emphasise is that for each firm we have only a single observation for training costs, namely 1997. Second, although 500 firms indicated some form of formal training in 1997, we only have 220 non-missing observations of training costs for firms with employment data in 1995. Subsequently, if we first assume that firms which *do not* provide this data are, on average, identical to those which respond, then we have a simple efficiency loss in terms of the subsequent fall in sample size. Thus, although in one instance we can point to an efficiency gain in terms of the higher information content of the training cost variable, we need to account for the fact that we have fewer observations to identify any additional effect of training costs. Obviously to the extent that data is missing non-randomly we need to account for possible biases.

In table 4 we examine the relationship between employment growth (EG), firm size (EMPL_{87} and EMPL_{90}) and training frequency (D_{91} and D_{97}) for the two periods 1987-90 and 1990-95. In order to examine the nature of these relationships across the distribution of growth rates, we calculate average values based upon deciles of employment growth. These relationships are also presented in Figures 1 and 2. For both the periods 1987-90 and 1990-95 there is a negative relationship between the proportional growth of a firm and initial size. This confirms our prior expectations and, in addition, the findings of Hart and Oulton (1992) who, using UK data for the period 1989-93, demonstrated that small firms generated proportionately more jobs than larger companies. In a follow-up study (see Hart and Oulton (1996)) the authors demonstrate that this finding is robust to both sectoral and class size disaggregation, in keeping with the earlier UK results for the 1980's (see Dunne and Hughes (1994) and Cosh, Hughes, Lee, and Pudney (1998)). For both 1987-90 and 1990-95 we observe a general negative but non-monotonic relationship. If we compare figures 1(a) and 1(c) and figures 2(a) and 2(c), we also observe that firm size is a good indicator of the decision to undertake training. Thus, given the inverse relationship between employment growth and firm size, we can view the role of training as a marginal effect once we control for initial size.

The relationship between training and employment growth is observed to depend upon when training is measured. In examining employment growth over the period 1987-90 our training indicator is measured in 1991, and for the years 1990-95 we have two measures of training: 1991 and 1997. In Figure 3 we present kernel density plots of employment growth over the period 1990-95, differentiating between the year of the training indicator and trainers and non-trainers. Figure 3 confirms the findings of Cosh, Duncan, and Hughes (1998), namely that the difference between employment growth of trainers and non-trainers is negligible when training is measured in 1991. When our training measure is based upon 1997 data we do observe a difference.

In Figures 2(a) and 2(b) we present the *marginal* frequencies for training propensity (measured in 1991 and 1997) across the deciles of employment growth. For the training indicator based upon 1991 data we do not observe any identifiable relationship between training and firm performance. In contrast, the training measure for 1997 suggests a relatively strong relationship, with the exception of a group of mid sized firms. If we move from marginal to joint frequencies based upon considering training decisions in both 1991 *and* 1997, we observe a number of interesting features. Figure 4 presents this data, and we examine the issue of both training persistence and firms which either train (not-train) in 1991 and cease (begin) training in 1997. We again emphasise that our use of the term persistence is an abuse of the vernacular, given that we do not have a complete set of time series observations over the period 1991-1997. Firms which are persistent trainers do not seem to exhibit a clear trend with regards growth of employment. The most notable trend is exhibited by firms which were training in 1991 but not in 1997. In this instance there is a clear negative relationship insofar as the highest frequency of firms in this state are observed in the lowest employment growth deciles. Note also that firms which started training in 1997 were more concentrated in the upper deciles of the employment growth distribution (see Figure 4(c)).

6 Firm Performance and Training: Results from a Two Period Model of Employment Growth

In Table 5 we present our results based upon the estimation of a two period model of employment growth given by (5) and (6) and (12)[4]. We present results for eight variants labelled i) to viii) and focus upon the following outputs: γ is a measure of convergence and represents the effect of initial employment size T_{91}, T_{97} and T_{9197} represent the effect of training on employment growth with training (measured using a simple binary indicator) recorded in 1991, 1997 and in both periods. λ represents the correction for the potential endogeneity of the training decision.[5] Given that the generalised residuals are positive

[4]Note that the use of a two-step Heckman procedure to correct for sample selection provides consistent parameter estimates for the employment growth equation. However, estimates of standard errors are inconsistent.

[5]A formal test of a null of no attrition bias due to firm failure in the size gowth relationship was also carried out. Based upon the same method used to test for the endogeneity of training the null could not be rejected at the 5% level. This test was performed in a conditional fashion in that a control for the endogeneity of training was also conducted. We

by construction we can provide an interpretation based upon the sign of this coefficient. If $\lambda > 0$ (< 0), this indicates that unobserved factors which lead to a high propensity to train also result in a higher (lower) level of performance. Subsequently if we do not account for this correlation we will consistently overestimate (underestimate) the effects of training on performance. $\Pr > F$ and $\Pr > \chi^2$ are the p values for the Ramsey Reset (omitted variable) test and heteroscedasticity. Parameter estimates presented in square brackets are robust estimates based upon the use of an observation specific set of weights which downweight the influence of outlier observations.[6]

In evaluating the results in Table 5 it is important to bear in mind the following. First, our regression results are presented in three sections. Section I presents results for models when we utilise a binary training indicator measurement in *either* 1991 or 1997. Section II incorporates *both* measures of training and allows us to differentiate between firms which were observed to train (not train) in both periods and those firms which trained (did not) in 1991 and were not training (training) in 1997. In Section III we consider the added value of including a measure of training costs. Note also that A indicates that the sample consists of firms which were alive in both 1987 and 1990; B indicates all firms which were alive in 1987, 1990 and 1997. Thus, results i) and ii) allow an informal evaluation of the impact of survival bias when comparing parameter estimates across the two periods.[7]

In both periods, and across all variants, the hypothesis that small firms grow faster than larger firms cannot be rejected. If we compare variant ii) with the OLS estimates for variant iii) we note that the rate of convergence is significantly higher for the 1987-90 period relative to 1990-95. One of the reasons for this is that a law of proportionate effect specification becomes less

note that in this study controls for endogeneity and sample attrition bias due to business failure have been applied assuming that these two factors are independent.

[6]The precise form of the robust estimator used in this application is based upon the work of Goodall (1983) and Rousseeuw and Leroy (1987). We first estimate the regression using standard least squares and using Cooks D we exclude observations for which $D > 1$. Following this the algorithm procedures iteratively applying both Huber weights (see Huber (1964)) and biweights (see Andrews, Bickel, Hampel, Huber, Rogers, and Tukey (1972)).

[7]A formal test of a null of no attrition bias due to firm failure in the size gowth relationship was also carried out. Based upon the same method used to test for the endogeneity of training the null could not be rejected at the 5% level. This test was performed in a conditional fashion in that a control for the endogeneity of training was also conducted. We note that in this study controls for endogeneity and sample attrition bias due to business failure have been applied assuming that these two factors are independent.

persuasive as the period of employment change increases, since the impact of the initial value will decay with time. Evidence of this is found from the size of the coefficient on lagged employment. For both periods we find a significant training effect if we measure training at the *end* of the period (compare variants i), ii) and iv) with iii)). However, if we utilise robust regressions and thereby seek to discriminate between 'good' and 'bad' parts of the sample, we find a highly significant effect due to training. This is so even when training is measured at the beginning of the period. In a further analysis not reported here we found that for variant iii) the influential observations (i.e. those which were subsequently downweighted) were almost equally concentrated in the lower and upper deciles across the distribution of employment growth. However, this pattern was not present for the 1987-90 period and, in fact, influential observations were almost uniformly distributed over employment growth deciles.

In Section II we report results based upon analysis using the binary indicators of training in 1991 and 1997. Variant v) is based upon an approach in which the underlying model of the training decision is specified by differentiating between two groups: firms which were observed to train in both periods, and all others. Using the robust estimator we find a strong significant effect due to persistent trainers over and above the residual category. In variant vi) we examine whether we can differentiate between the persistent trainers and the three remaining groups taken separately. The 3 (dummy) variables (T_P, T_B and T_C) represent the impact on employment growth of persistent trainers (P), those which began (B) training in 1997 and those firms which ceased training in 1997 (C), *relative* to the base category non-trainers. Thus, we record a highly significant difference between persistent trainers and non-trainers, and firms which trained in 1997 and not in 1991, again relative to the referent group non-trainers. The difference between non-trainers and firms which trained in 1991 but were not training in 1997 was not significant.

The 1997 survey provides a wide range of information about management practices and attitudes. We have set out earlier the reasons for believing that training should be evaluated in the context of the overall set of human relations practices at work in a firm. We therefore examine the association of training in 1997 with these and other firm level characteristics in two ways. We carried out simple t-tests on the differences in means between trainers and non-trainers, and used the non-parametric Mann Whitney test to eliminate the impact of outliers. Our findings are presented in Table 6. We find no evidence that high profitability in 1995 has led to the adoption of training in 1997, in fact our findings suggest the reverse. Training firms are more likely to have people with professional qualifications running the business, place greater emphasis on design, quality, product range, marketing and flair as their sources of competitive advantage. They are also less likely to emphasise price and speed of service than non-trainers. The trainers, perhaps unsurprisingly, are significantly more likely to identify skill shortages as an inhibitor of their growth performance.

Trainers are far more likely to have sought external advice to support their training activities. About three quarters of them had drawn upon external advice and about one half had used Business Links. Our results also suggest that trainers have more sophisticated management than non-trainers. Thus they are far more likely to use investment appraisal methods. However, for our purposes it is their human resource management which is of particular interest. All aspects of human resource management are significantly more prevalent amongst trainers. This raises the question of the interaction between these aspects and the impact of training on performance.

Of particular interest is the impact of the use of total quality management and quality circles in conjunction with training on firm performance, differentiating firms, as before, according to the training categories T_P and T_B. Given that data on human resource management are only available for 1997, we are able to identify four categories of firms. Persistent trainers which do not use either technique we denote T_PS_0; persistent trainers which are using these practices are denoted T_PS_1. Firms which began training in 1997 are divided into similar categories, namely T_BS_0, T_BS_1. These four groups are compared with non-trainers in 1997 and the results are presented in Table 7. The results suggest that the impact of training is dependent on the labour practices within which it is embedded. Thus, we find that the impact of training on employment growth is significant only when associated with the adoption of more sophisticated human resource management techniques. This is true both for persistent trainers and for those which began training in 1997. Training without the adoption of such practices is associated with a positive, but insignificant, impact on growth performance.

In Table 8 we present the results from estimating a multinomial choice model of the joint frequencies over the D_{91} and D_{97} variables. The referent category is those firms observed *not* to train in both periods. Our results are consistent with expectations insofar as the biggest difference in terms of the impact of firm level variables upon the probability of belonging to the four training states, is between the persistent and the non-trainers (referent group). The positive coefficients for *lempl*, *innov* and *skill* indicate that initial employment size, innovation activity and the existence of recruitment problems in certain skill categories are all significant indicators of persistent training, relative to non-training. For the other two categories (train_{97} not train_{91}, not train_{97} train_{91}) we observe a similar positive effect due to initial employment size, and for those firms which were not observed to train in 1997 there is a significant effect of the recruitment variable, *skill*.

In Section III we examine the extent to which including a measure of training intensity provides additional information over and above the binary indicators of training. Results vii-viii are based upon estimating the censored regression models given by (12) and using the generalised residuals to correct for endogeneity. In interpreting the effect of the training costs variable we should consider the fact that although over 500 firms supplied information on employment, training and related characteristics for 1990 and 1995, only 266 firms responded to the training cost question. Subsequently, although there is obviously a theoretical information gain with regards the use of training costs data relative to simple binary indicators of training provision, the loss of observations through item non-response will reduce the precision with which we can estimate any effect.

In results vii we include only the training cost variable *Tcost*, and find a significant impact of training expenditure on employment growth. In viii we include both measures of training, namely the 3 dummy variables T_P, T_B and T_C together with *Tcost*. Once we control for the *qualitative* effects of the decision to train, we still find a significant effect for the training costs variable, but at a reduced level of significance.

7 Conclusions

Our empirical and methodological findings have four major implications. These relate respectively to: the measurement of training; the identification of the wider human relations management context in which training occurs; the virtues of including a panel element in data collection practices; and the need to adopt robust modelling techniques which address both the extreme heterogeneity of small and medium sized business performance and the appropriate treatment of sample selection biases, and the endogeneity of the training decision.

It is important in designing data collection protocols for evaluating the impact of training that measures of the intensity of training are included alongside measures of the incidence of training. These need to be included as a part of the information system design for all participants in schemes from the outset, and in designing control group information collection. Care needs to be taken, however, in question design to maximize item response rates to such questions. This is because there is a trade off between the increased efficiency of the underlying econometric estimate of the impact of training and the adverse impact reduced sample sizes cause if low item response rates occur. This suggests that pilot studies should be carried out to identify the most meaningful and readily answered questions to ask on training intensity.

The results support the argument put forward in detail in Hughes and Weeks (1999) that the human relations context can have an important conditioning impact on the estimated role of training in affecting firm performance. Information on these aspects of firm characteristics should also be incorporated in training scheme information systems, alongside information on past involvement in such activities. Similar issues of question design arise as in the case of measuring training intensity.

The inclusion of a panel element in information system design is also of great significance. It generates extra data points which allow for the incorporation of dynamic elements to the econometric methodology. Our report shows that this is important in relation to the analysis of endogeneity and causation. It is also revealed as essential if questions about the decision to start, stop and continue training are to be addressed. Each of these are important in a policy context.

The report reveals that the adoption of robust regression techniques is of great importance in the context of the heterogeneous population of small and medium sized firms with relatively volatile performance characteristics. Conventional OLS techniques may mask the relationships which exist in a central core of the observations under investigation. Our results also reveal the importance of corrections for the endogeneity of training in the evaluation of the latter on performance. They also reveal that considerable insights can be obtained from repeated panel cross sections even if they are not carried out on an annual or even shorter cycle. It is possible in this context to consider questions in surveys which elicit answers on training activity in a series of intervening years even if the timing of each survey is biennial.

The research has focused on a single measure of performance (employment growth). It has also, because of the agreed limited scope of the research brief, explored a limited range of interactions between training and the human relations and other relevant variables in the CBR dataset. A study with a longer time frame could investigate the interrelationship between training on the one hand, and business survival, innovative activity, and measures of performance based on profitability and productivity on the other. Each of these is possible with the augmented 1987-1997 CBR dataset used in this report.

Within a non-experimental setting the determination of whether a particular policy is deemed successful is increasingly viewed in terms of whether a positive mean impact can be identified, as opposed to learning about structural parameters. In this regard it would be instructive to consider a number of alternate outcome measures of the impact of training on performance. For example, if we view both training frequency and intensity as being affected by employment policy, then counterfactual simulations can be utilised to determine the impact of, for example, the introduction of a training subsidy designed to raise the proportion of firms engaged in training. These outcome measures will also facilitate a more direct comparison across different model specifications.

8 Appendix

CAGE:	chief executive age in years (1991 survey)
COMPS:	number of serious competitors
EG_{8790}:	employment in 1990/employment in 1987
EG_{9095}:	employment in 1995/employment in 1990
$EMPL_{tt}$:	employment level in 19tt
GROWTH:	variable which measures the firm's growth objectives on a scale of 1-4
INNOV:	binary variable which equals 1 if the firm innovated during the last 5 years, and zero otherwise (1991 Survey)
LARGEST:	% of sales to largest customer (1991 survey)
$LEMPL_{87}$:	natural log of employment 1987
$LEMPL_{90}$:	natural log of employment 1990
LENTAGE:	natural log of enterprise age in 1995
RSKILL:	ratio of managers and higher professionals to total employment (1991 survey)
SEC(N)DUM:	11 industrial sector dummies (N=1,...,11)
SEC1:	chemicals man-made fibres, rubber and plastics
SEC2:	metal goods and mechanical engineering

SEC3: electrical and instrument engineering

SEC4: food drink and tobacco

SEC5: textiles, leather footwear and clothing

SEC6: timber furniture, etc.

SEC7: paper, printing and publishing

SEC8: metals minerals and other manufacturing

SEC9: advertising and management consultancy

SEC10: technical and professional consultancy services

SEC11: other services

SKILL: binary variable equals 1 if the firm is finding it difficult to recruit in certain skill categories, and zero other (1991 Survey)

TCOST: expenditure on training as a percentage of sales (1997 Survey)

T_{91}/D_{91}: binary variable equals 1 if the firm provided formal training in 1991 and zero otherwise

T_{97}/D_{97} binary variable equals 1 if the firm provided formal training in 1997 and zero otherwise

T_P: binary variable equals 1 if the firm provided training in both 1991 and 1997 and zero otherwise

T_B: binary variable equals 1 if the firm provided training in 1997 but not in 1991 and zero otherwise

T_C: binary variable equals 1 if the firm provided training in 1991 but not in 1997 and zero otherwise

Y: natural log of employment growth for 1987-90 or 1990-95

Notes: Any of the above terms appearing with 'sq' implies the square. of the term. For example, RSKILLSQ=RSKILL *RSKILL.

References

ANDREWS, D. F., P. J. BICKEL, F. R. HAMPEL, P. J. HUBER, W. H. ROGERS, AND J. W. TUKEY (1972): *Robust Estimates of Location: Survey and Advances.* Princeton University Press, Princeton, NJ.

ARTHUR, J. (1994): "Effects of Human Resource Systems on Manufacturing Performance and Turnover," *Academy of Management Journal*, 37, 670–87.

ASHENFELTER, O., AND D. CARD (1985): "Using the Longitudinal Structure of Earnings to Estimate the Effect of Training Programs," *Review of Economics and Statistics*, 67(4), 648–60.

BAILEY, T. (1993): "Organizational Innovation in the Apparel Industry," *Industrial Relations*, 32, 30–48.

BASSI, L. (1983): "Estimating the Effect of Training Programs with Non-Random Selection," *The Review of Economics and Statistics*, pp. 36–43.

BLACK, S., AND L. LYNCH (1997): "How to Compete the Impact of Workplace Practices and Information Technology on Productivity," Working Paper Series, National Bureau of Economic Research, Inc.

COSH, A., J. DUNCAN, AND A. HUGHES (1997): "Investment in Training and Small Firm Growth and Survival," Research Report, ESRC Centre for Business Research, University of Cambridge.

——— (1998): "Investment in Training and Small Firm Growth and Survival," Research Report, (RR36) DfEE, Sheffield, January.

COSH, A., AND A. HUGHES (1998): "Enterprise Britain: Growth Innovation and Public Policy in the Small and Medium Enterprise Sector," ESRC Centre for Business Research, University of Cambridge, Cambridge.

COSH, A., A. HUGHES, K. LEE, AND S. PUDNEY (1998): "Semi-Parametric Estimation of the Comapany Size Growth Relationship," in *Applied Economics and Public Poilcy*, ed. by I. Begg, and B. Henry, pp. 107–144. DAE Occasional Paper No. 63, Cambridge University Press.

DUNNE, J. P., AND A. HUGHES (1994): "Age, Size, Growth and Survival: UK Companies in the 1980's," *Journal of Industrial Economics*, LX11(1).

GOODALL, C. (1983): "M-Estimators of Location: An Outline of the Theory," in *Understanding Robust and Exploratory Data Analysis*, ed. by D. C. Hoaglin, F. Mosteller, and J. W. Tukey, pp. 339–431. John Wiley and Sons, New York.

HART, P. E., AND N. OULTON (1996): "Growth and Size of Firms," *The Economic Journal*, 106, 1242–52.

HECKMAN, J., AND R. ROBB (1985): "Alternative Methods for Evaluating the Impact of Interventions: An Overview," *Journal of Econometrics*, 30, 239–267.

HUBER, P. J. (1964): "Robust Estimation of a Location Parameter," *Annals of Mathematical Statistics*, 35, 73–101.

HUGHES, A., AND M. WEEKS (1999): "Methodological Approaches to the Study of the Impact of Training on Firm Performance," Centre for Busines Research and Department of Applied Economics, University of Cambridge (mimeo).

HUSELID, M. (1995): "The Impact of Human Resource Management Practices on Turnover, Productivity, and Corporate Financial Performance," *Academy of Management Journal*, 38(3), 635–672.

ICHNIOWSKI, P., K. SHAW, AND G. PRENNUSHI (1995): "The Effects of Human Resource Management Practices on Productivity," NBER Working Paper No. 5333, November.

KELLEY, M. (1994a): "Information Technology and Productivity: The Elusive Connection," *Management Science*, 40, 1406–25.

——— (1994b): "Participative Bureaucracy and Productivity in the Machined Products Sector," *Industrial Relations*, 35, 374–399.

MILGROM, P., AND J. ROBERTS (1995): "Complementarities and Fit: Strategy, Structure and Organizational Change in Manufacturing," *Journal of Accounting and Economics*, 19, 179–208.

ROUSSEEUW, P. J., AND A. M. LEROY (1987): *Robust Regression and Outlier Detection*. John Wiley and Sons, New York.

Storey, D., and P. Westhead (1997): "Training Provision and the Development of Small and Medium Sized Businesses," Department of Education and Employment Research Report RR26, HMSO Sheffield.

TABLES AND FIGURES

Table 1: Training and Employment Growth

1987-90
Training Measured in 1991

$H_0 : \overline{EG}^1_{8790} = \overline{EG}^0_{8790}$

$H_1 : \overline{EG}^1_{8790} > \overline{EG}^0_{8790}$

p-value 0.0006

1990-95
Training Measured in 1991

$H_0 : \overline{EG}^1_{9095} = \overline{EG}^0_{9095}$

$H_1 : \overline{EG}^1_{9095} > \overline{EG}^0_{9095}$

p-value 0.9482

1990-95
Training Measured in 1997

$H_0 : \overline{EG}^1_{9095} = \overline{EG}^0_{9095}$
$H_1 : \overline{EG}^1_{9095} > \overline{EG}^0_{9095}$

p-value 0.0000

Table 2: The Persistence of Training and Employment Size

	Average Employment $\overline{EMPL_{95}}$	Count	(%)
Training States			
$\overline{D}_{91} \cap \overline{D}_{97}$	19.78	118	(17)
$D_{91} \cap D_{97}$	80.39	363	(53)
$D_{91} \cap \overline{D}_{97}$	34.36	118	(17)
$\overline{D}_{91} \cap D_{97}$	29.01	88	(13)
		687	

D_t ($\overline{D}_t$) = train (not train) in time t.

Table 3: Training Costs and Employment Size

Training costs as proportion of labour costs	Average Employment $\overline{EMPL}_{95}$	Freq.	(%)
less than 1%	44.30	49	(22)
1%	46.81	54	(24)
2%	47.02	48	(22)
3%	66.93	32	(15)
4%	80.25	8	(4)
5%	88.15	13	(6)
6% or more	136.62	16	(7)
		220	

Table 4: Employment Growth, Training Frequency and Firm Size: Means by Deciles (F_i) of Employment Growth

	1987-90			1990-95			
	D_{91}	EG_{8790}	$LEMPL_{87}$	D_{91}	D_{97}	EG_{9095}	$LEMPL_{90}$
F_1	0.496	-0.649	3.082	0.724	0.521	-0.952	3.283
F_2	0.738	-0.146	3.713	0.652	0.536	-0.379	3.091
F_3	0.491	-0.004	2.631	0.691	0.588	-0.201	3.335
F_4	0.805	0.080	4.091	0.779	0.735	-0.094	3.844
F_5	0.774	0.184	3.327	0.571	0.591	-0.006	2.798
F_6	0.840	0.278	3.288	0.775	0.700	0.062	3.900
F_7	0.696	0.382	2.760	0.783	0.698	0.166	3.482
F_8	0.672	0.586	2.470	0.741	0.685	0.303	3.123
F_9	0.720	0.876	2.330	0.716	0.776	0.481	2.764
F_{10}	0.706	1.618	1.550	0.632	0.764	0.968	2.450

Table 5: Impact of Training on Firm Performance

	Period	γ						λ		N		
						Section I: Training 1991 or 1997[1,2]						
	Period	γ	T_{91}	T_{97}	T_{9197}			λ	$\bar{R}^2$	N	Reset Pr > F	Hetero Pr > χ^2
i)	1987-90 A	-0.369**	2.751**	-	-	-	-	-1.615**	0.648	1,011	0.000	0.000
		[-0.318**]	[2.364**]			-	-	[-1.389**]				
ii)	1987-90 B	-0.317**	1.743**	-	-	-	-	-0.962**	0.410	502		
		[-0.208**]	[1.151**]	-	-	-	-	[-0.622**]		502		
iii)	1990-95 B	-0.078**	0.239	-	-	-	-	-0.107	0.067	522	0.443	0.191
		[-0.083**]	[0.393**]			-	-	[-0.262**]				
iv)	1990-95 B	-0.067**	-	0.179**	-	-	-	0.007	0.087	522	0.679	0.026
		[-0.127**]		[0.181**]		-	-	[0.017]				
						Section II: Training 1991 and/or 1997						
	Period	γ	T_P	T_B	T_C	T_{9107}		λ	$\overline{R}^2$	N	Pr > F	Pr > χ^2
v)	1990-95 B	-0.089**	-	-	-	0.285	-	-0.081	0.102	522	0.799	0.111
		[0.089**]			-	[0.350**]		[-0.124]				
vi)	1990-95 B	-0.065**	0.187**	0.144*	-0.043	-	-	NA	0.115	522	0.794	0.181
		[-0.059**]	[0.206**]	[0.154**]	[0.016]	-	-					
						III Training Intensity 1997						
	Period	γ	T_P	T_B	T_C	Tcost		λ	$\overline{R}^2$	N	Pr > F	Pr > χ^2
vii)	1990-95 B	-0.055**	-	-	-	0.027*	-	-0.002	0.077	355	0.654	0.058
		[-0.063**]	-	-	-	[0.038**]	-	[-0.001]		355		
viii)	1990-95 B	-0.051**	0.107	0.005	-0.026	0.081	-	-0.003	0.080	355	0.871	0.244
		[-0.065**]	[0.141]	[-0.001]	[0.019]	[0.087*]	-	[-0.006]		355		

1 Note: the measure of fit $\overline{R}^2$ is not available for the robust regressions.
2 Regressions i) to viii) include, apart from the results reported, the following set of covariates log of initial level of employment ($LEMPL_{87}$ or $LEMPL_{90}$), % of sales to largest customers ($LARGEST$), the age of the chief executive in years ($CAGE$), the log of the age of the enterprise ($LENTAGE$), and number of serious competitors ($COMPS$), sector dummies ($SEC_i, i = 1, ..., 11$). See Appendix.

Table 6: Differences in Firm Characteristics: Trainers vs. Non-trainers, 1997

	Mean Values		Mann Whitney Test
	Trainers	Non-trainers	Significance Level
General			
Profit Margin 1995 %	8.85	13.89(***)	.0065(***)
% with CEO holding degree or professional qualification	53.5	37.6***	.0018***
Human Resources Management			
% of firms using:			
Total quality management	44.8	14.2***	.0000***
Quality circles	20.6	7.1***	.0024***
Job rotation/multi-skilling	44.8	20.7	.0003***
Performance related pay	38.1	25.8***	.0041***
Competitive Advantage			
Source of main competitive advantage on scale of 1-5			
Price	2.57	2.92(***)	.0027(***)
Marketing	2.82	2.41	.0007***
Speed of service	3.72	4.01(***)	.0053(***)
Reputation	4.10	4.10	.4648
Cost	2.75	2.92	.1672
Design	3.49	3.14***	.0089***
Quality	4.12	4.03	.2942
Specialism/niche	4.07	3.90*	.1092
Range	3.77	3.42***	.0006***
Flair	3.35	3.03***	.0047***
Personal attention	4.33	4.46	.1063
Growth Inhibitors			
Significance of factors limiting growth on scale 1-5			
Skilled labour	2.47	2.10***	.0012***
Management skills	2.68	2.17***	.0000***
Marketing skills	2.71	2.47*	.0604*
External Advice (% of firms seeking external support)			
Staff training	69.9	15.8***	.0000***
Business Links - training/IIP	46.3	15.0**	.0124**
Financial support - IIP	19.7	3.0***	.0000***
Investment Appraisal			
% using payback	59.9	43.4***	.0050***
% using DCF methods	19.9	5.9***	.0036***

* 10% significance level
** 5% significance level
*** 1% significance level
() shows cases where the average value for non-trainers is greater than that for trainers

Table 7: Impact of Training on Firm Growth in Association with use of TQM and/or Quality Circles

Section II: Training and Management Practices		
Variable	OLS	Robust Regression
γ	-0.098**	-0.099***
T_PS_0	0.049	0.066
T_PS_1	0.186**	0.196***
T_BS_0	0.081	0.069
T_BS_1	0.250**	0.255**
$\overline{R}^2$	0.095	-
N	281	281

See footnote to Table 5.

Table 8: Log Likelihood

Variable	Coeff.	t-stat	$P > \|t\|$
Persistent			
lempl	1.228	7.771	0.000
growth	0.161	0.693	0.488
lentage	-0.302	-1.737	0.082
innov	1.148	4.052	0.000
skill	1.165	3.814	0.000
rskill	2.314	1.270	0.204
rskillsq	-3.409	-1.701	0.089
cage	-0.010	-0.671	0.502
largest	-0.132	-1.072	0.284
comps	0.005	0.825	0.409
_cons	-2.780	-2.255	0.024
D_{97} *not* D_{91}			
lempl	0.724	3.960	0.00
growth	0.420	0.149	0.882
lentage	-0.397	-1.771	0.077
innov	-0.005	-0.016	0.987
skill	0.160	0.409	0.683
rskill	1.420	0.697	0.486
rskillsq	-0.706	-0.340	0.734
cage	0.009	0.452	0.651
largest	-0.085	-0.572	0.567
comps	.003	0.373	0.709
_cons	-2.025	-1.371	0.170
D_{91} not D_{97}			
lempl	0.606	3.702	0.000
growth	0.124	0.485	0.628
lentage	-0.076	-0.409	0.682
innov	0.508	1.658	0.097
skill	0.699	2.110	0.035
rskill	-1.735	-0.916	0.360
rskillsq	0.472	0.223	0.823
cage	0.007	0.418	0.676
largest	-0.134	-0.996	0.319
comps	-0.004	-0.456	0.648
_cons	-1.807	-1.369	0.171

Figure 1: Training and Employment Size by Deciles of Employment Growth: 1987-90

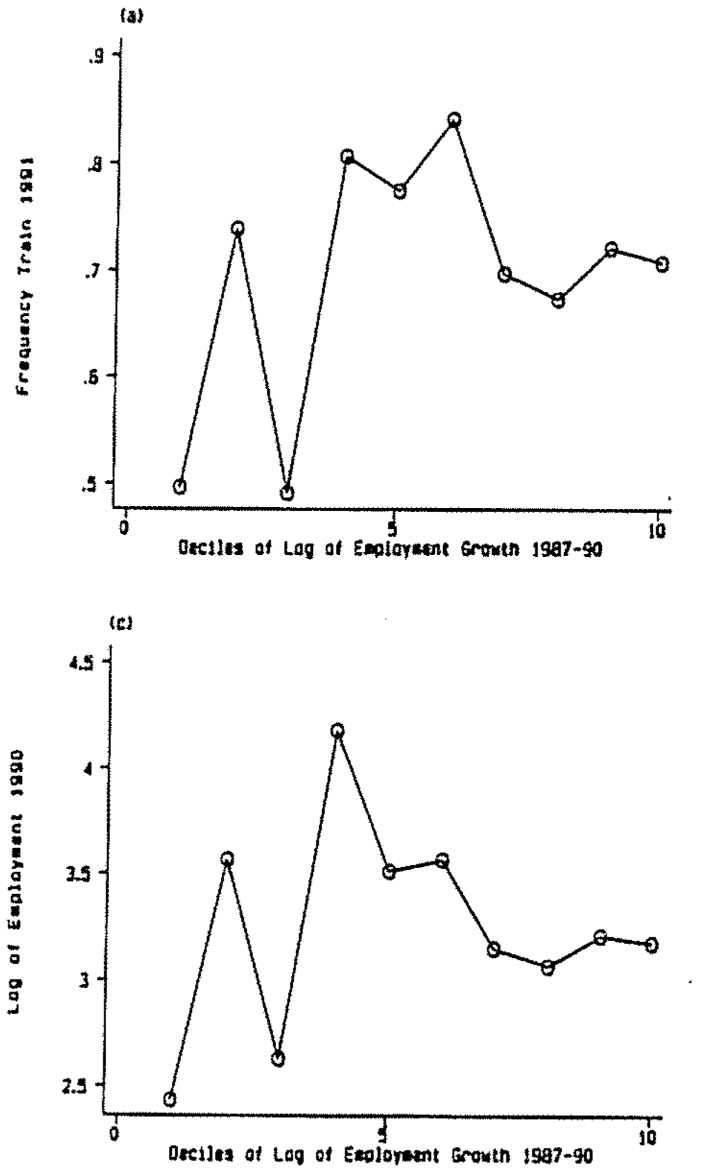

Figure 2: Training and Employment Size by Deciles of Employment Growth: 1990-95

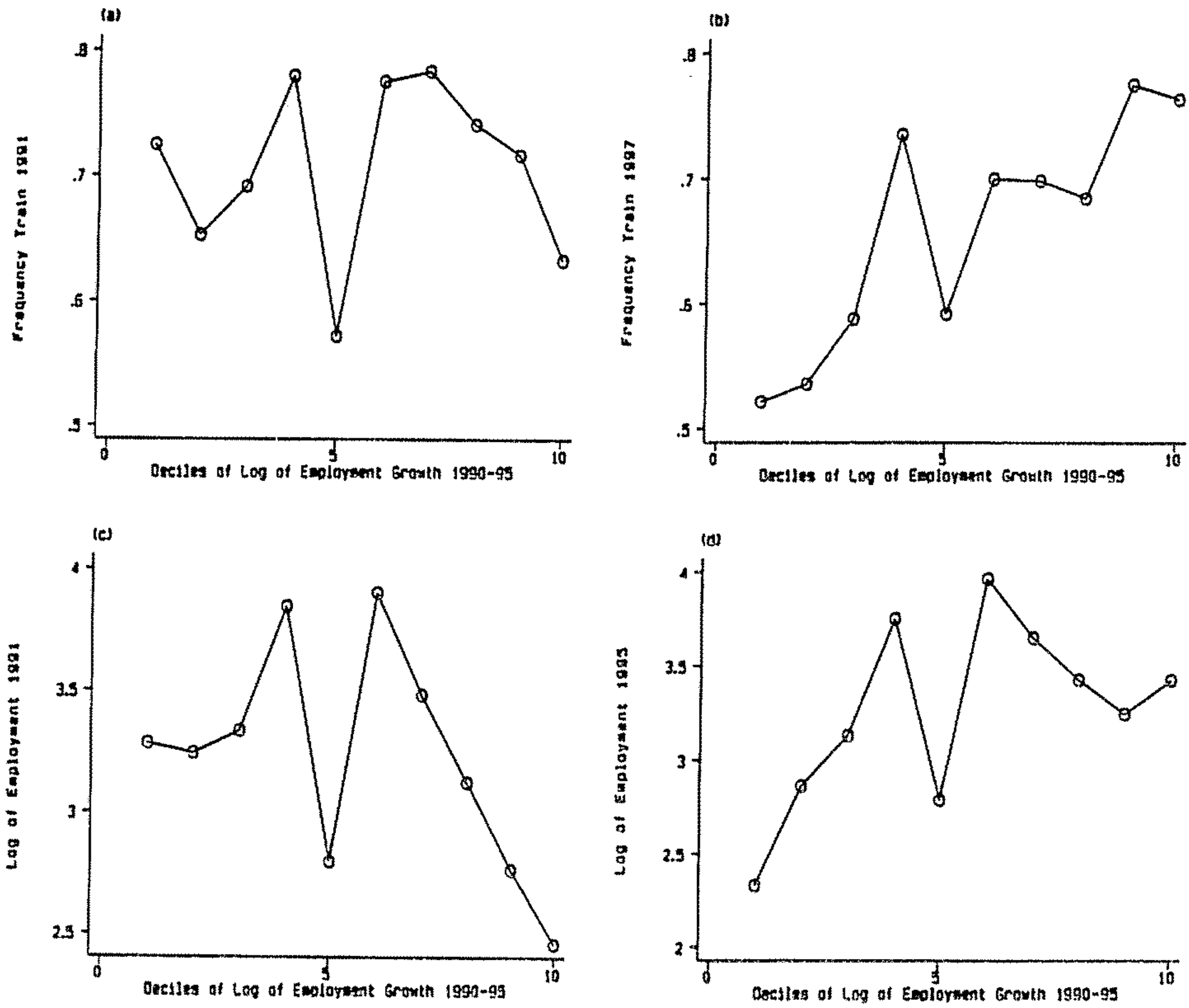

Figure 3: Kernel Density Employment Growth by Training Measures

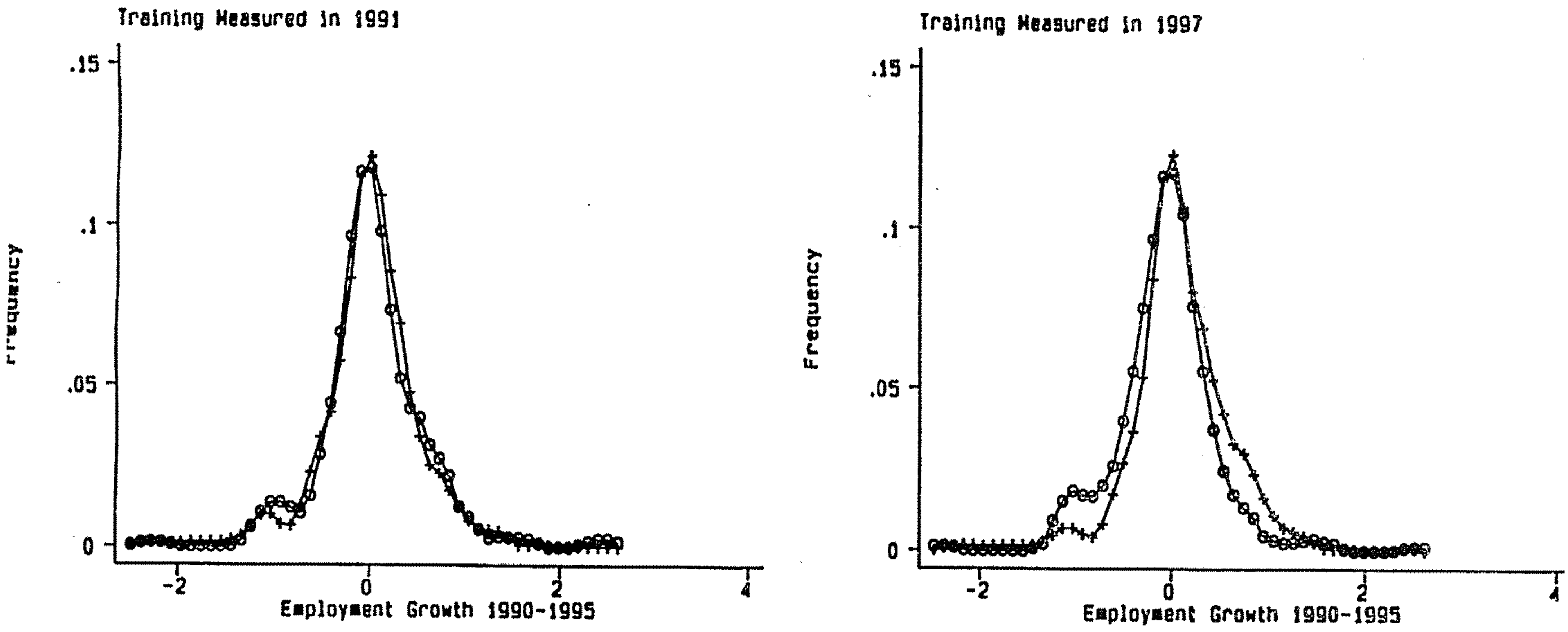

Figure 4: Training Propensity: 1991 and 1997