

# **FIRM-RELATED TRAINING TRACKS: A RANDOM EFFECTS ORDERED PROBIT MODEL \***

by

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## **Abstract**

A random effects ordered response model of training is estimated to analyze the existence of training tracks and time varying coefficients in training frequency. Two waves of a Dutch panel survey of workers are used covering the period 1992-1996. The amount of training received by workers increased during the period 1994-1996 compared to 1992-1994. Evidence is found for the existence of training tracks in the amount of training courses taken. It is further found that the effects of individual characteristics such as education, age and gender on training should be treated as individual varying coefficients.

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# 1 Introduction

During the past decade, employers and employees have become increasingly aware of the importance of firm-related training. In many European countries unions have made training for workers part of their collective wage bargaining agreements with firms. The main aim for unions is to have firms provide training for all workers. The underlying idea is that training makes skilled workers more scarce and that this will enable unions to negotiate higher wages for them.

The increased importance attached to firm-related training has contributed to a growing attention to the determinants of participation in firm-related training. Access to training is not the same for everyone. There is substantial evidence that some workers are offered more opportunities for investment in training than others.<sup>1</sup> It is found that the amount of training received varies across workers. The probability of receiving training is generally found to increase with ability characteristics such as the level of education, decreases with age and is higher for male workers than for female workers. For a survey on the literature on the participation in firm-related training, see Groot (1999) and Groot & Maassen van den Brink (1998).

Until now, empirical research in this area has mainly focused on analyzing differences in participation in training between workers with different characteristics.

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<sup>1</sup> See, Alba-Ramirez (1991); Altonji & Spletzer (1991); Arulampalam, Booth & Elias (1996, 1998); Arulampalam & Booth (1997); Bartel (1995); Bartel & Sicherman (1995); Blundell, Dearden & Meghir (1994); Booth (1991); Greenhalgh & Mavrotas (1994); Groot (1994); Groot, Hartog & Oosterbeek (1994); Groot & Oosterbeek (1995); Groot & Maassen van den Brink (1997); Hill (2001); Kennedy, Drago, Sloan & Wooden (1994); Lynch (1992); Mincer. (1989); Koning, Gelderblom, Hammink, & Olieman (1991); OECD (1991); Oosterbeek (1996, 1998); Teulings & Budil-Nadvornikova (1989); Theodossiou & Williams (1995); Wooden (1992, 1996).

As a result we are able to say with some degree of confidence that on average higher educated workers, younger workers and male workers are more likely to receive training. Little is known about the variation in the frequency in training incidence among workers with certain characteristics. Are all higher educated young male workers likely to receive training, or are some of them more likely to be trained than others? Is the training intensity of these workers always higher than average? Are there groups of workers who receive more training than others all the time or only some of the time? Is participation in training correlated over time and does participation in training in one period increase the likelihood of receiving training in the next period as well? In other words, are there workers who can be said to be on a training track? And if some workers are on a training track, how does this relate to differences in observable individual characteristics such as education, age and gender? These are the questions that are addressed in this paper.

The object of this study is to analyze variation among workers of a certain education and age group and to establish the inter-temporal correlation in training frequency. A high inter-temporal correlation in training among workers strengthens the argument that training increases inequality between workers. As investments in human capital - such as training - increase wages and the chances of work, differences in training intensity increase social inequality (wage inequality, employment opportunities, etc.). As a result a positive inter-temporal correlation in training frequency might be an additional source of labor market segmentation. Not only may the inequality in employment and earnings opportunities increase because of differences in individual observable characteristics (education, age, gender), if some workers are on a training track this can be a source of inequality as well.

Training tracks create an inter-temporal correlation in the participation in training. There are two mechanisms by which a high and positive inter-temporal correlation in training increases inequality. First, a positive inter-temporal correlation strengthens the inequality generated by differences in access to training for some groups of workers. If, for example, higher educated workers are more likely to receive training all the time the effect of it will be larger than if higher educated are only more likely to receive training only some of the time. Second, a high inter-temporal correlation in training participation may result in increased inequality among workers with certain characteristics, if some of these workers are more likely to receive training all the time while others are not. If some higher educated are more likely to receive training frequently while other higher educated are not, higher educated workers may on average receive more training than lower educated workers. However, if the incidence of training is distributed unequally among higher educated workers, a positive inter-temporal correlation in training participation will result in inequality in wages and employment opportunities *among* these higher educated workers as well, and not just *between* higher and lower educated workers.

The outline of this paper is as follows. In order to analyze the inter-temporal correlation in training frequency a random effects ordered response model of investments in training is described in Section 2. In the empirical analysis, we use two waves of a longitudinal data set for the Netherlands. This allows us to analyze the evolvement of training over time. To the best of our knowledge there are no studies that have looked at how participation in training of individual workers changes over time. The data are described in Section 3. The data on training frequency refer to the number of training

courses taken by individual workers over a two years period. The number of training courses taken by workers is an ordinal variable, hence the use of an ordered probit model in the estimations. We test for the robustness of our findings by fitting some poisson regression equations on the number of training courses taken as well. As we use two waves of panel of workers, we observe training frequency over a four year period. The estimation results are presented in Section 4. Section 5 concludes.

## 2 A model of training investment

According to human capital theory, agents invest in training courses if the discounted present value of the benefits exceeds the costs of training. Decisions on firm-related training are taken jointly by the employer and the employee: the employer has the choice whether or not to offer training, the worker has to decide whether to accept the training offered. Since we have no information about this decision making process, the starting point of the empirical model is the training frequency function ( $T^*$ ). The training frequency of individual  $i$  ( $i=1, \dots, N$ ) in period  $k$  ( $k=1, \dots, K$ ) - i.e. the number of training courses taken during this specific period of time - is assumed to be determined by individual characteristics  $X_{ik}$ , characteristics of the firm  $Y_k$  and a individual specific term  $\mu_i$ :

$$T_{ik}^* = T_{ik}^*(X_{ik}, Y_{ik}, \mu_i)$$

To account for the joint involvement of employer and employee in training decisions, we assume that training frequency is a linear function of both individual ( $X_{ik}$ ) and firm ( $Y_{ik}$ ) characteristics:

$$T_{ik}^* = \beta_0 + \beta_1 X_{ik} + \beta_2 Y_{ik} + \mu_i + \varepsilon_{ik}$$

where  $\beta$  are coefficients that measure the impact of the characteristics  $X$  and  $Y$  on training  $T$ , and  $\varepsilon_{ik}$  is a normally distributed random error - with mean 0 and variance  $\sigma_\varepsilon$  - capturing unmeasured and unmeasurable effects on training. The random component  $\mu_i$  is distributed normally with mean 0 and variance  $\sigma_\mu$ .

Training frequency is a latent variable that is not directly observable. What we observe is the response to a question on the number of training courses taken. The observed training level  $T^o$  is analysed as a categorical ordered response variable.

The information on the number of training courses taken could also have been treated as a count variable. However, training courses may differ in the size and content. It is likely that there is a trade-off between the number of training courses taken and the amount of training per course, i.e. for workers who have taken many courses the average training intensity and duration per course is likely to be less than for workers who have received only few training courses. Hence, an ordered response model seems to be more appropriate than a mere count model on the number of training courses. We test for the choice of empirical model by comparing the results from the ordered probit equations with those of a poisson regression model.

The observed training level variable is assumed to be related to the latent training variable in the following way:

$$T_{ik}^o = j \text{ if } \alpha_{j-1} < T_{ik}^* \leq \alpha_j \quad j = 0, \dots, J$$

where  $J$  is the number of response categories and  $\alpha_i$  are threshold levels that are empirically estimated. This equation states that if training  $T_{ik}^*$  is between  $\alpha_{j-1}$  and  $\alpha_j$ , the response to the question on the number of training courses taken is equal to  $j$  ( $T_{ik}^o = j$ ).

The probability - for a given individual  $i$  - that  $T_{ik}^o = j$  (the response to the training

frequency question is j), conditional on  $\beta$  and  $\alpha$ , is given by:

$$Prob(T_{ik}^o = j | \beta) = \Phi\left(\frac{\alpha_j - z_{ik}}{\sigma_\varepsilon}\right) - \Phi\left(\frac{\alpha_{j-1} - z_{ik}}{\sigma_\varepsilon}\right)$$

where:

$$z_{ik} = \beta_0 + \beta_1 X_{ik} + \beta_2 Y_k + \mu_i$$

and  $\Phi(\cdot)$  represents the cumulative standard normal distribution function. For identification we set  $\alpha_1 = 0$  and  $\sigma_\varepsilon = 1$ . This is the specification of the well-known ordered probit model (McKelvey & Zavoina 1975).

The individual specific effect  $\mu_i$  is treated as a random effect and is assumed to be normally distributed. The random effect ordered probit model is estimated by maximum marginal likelihood estimation. The likelihood function is integrated with respect to the distribution of the parameters  $\beta_0$  and  $\mu_i$  to obtain a marginal likelihood free of the random parameter (see Agresti & Lang 1993). Let  $\theta = \beta_0 + \mu_i$ . The likelihood function  $L(\cdot)$  is given by:

$$L(T_{ik}^o) = \int_{\theta} \prod_{i=1} \prod_{j=1} [ \Phi(\alpha_j - z_{ik}) - \Phi(\alpha_{j-1} - z_{ik}) ]^{d_{ikj}} g(\theta) d\theta$$

where  $d_{ikj} = 1$  if  $T_{ik}^o = j$  and  $d_{ikj} = 0$  otherwise, and  $g(\theta)$  represents the distribution of the  $\theta$  vector in the population. For details about the maximum marginal likelihood estimation procedure, see Hedeker & Gibbons (1994). The estimation was done with MIXOR, a

Fortran based computer program for mixed-effects ordinal regression analysis (Hedeker & Gibbons 1996).

### 3 Data and descriptive analysis

The data for the empirical analysis are taken from the 1994 and 1996 waves of the Dutch OSA-Labor Market Survey. This data set is a longitudinal survey of individuals aged between 15 and 65 years. Interviews for the survey are conducted approximately every two years since 1985. Unfortunately we are only able to use the two last waves of the survey. The reason for this limitation is that the on-the-job training questions were phrased differently before 1994. Every wave of the sample contains about 4500 individual observations. From this survey we selected individuals who participated in the survey both in 1994 and 1996, and who were in paid employment at the time of both the interviews. This reduces the sample size to 3682 observations.

Training frequency is determined by the response to the following question: *AI want to ask you about courses. I mean course that you can take through your work as well as courses that are relevant for your possible work. How many of these courses have you taken since September 1 1992/1994?@* As both in 1994 and 1996 the respondents are asked about the number of courses taken during the two years before the interview, we observe the training frequency over a period of four years. The information on training frequency is limited to the number of training courses only. Ideally, we should like to take account for the duration and intensity of the training as well. The heterogeneity in the amount of training per course is accounted for by analysing the number of training courses taken as an ordered response variable rather than as a count variable. Compared to most previous studies on the determinants of firm-related training, our study has the advantage that we not only look at whether or not one participates in any training but also analyse the number of training courses

taken.

Only few studies have looked at the determinants of the frequency of training, i.e. the number of training courses taken. One of the exceptions is Arulampalam & Booth (1997). This study uses a hurdle negative binomial model to estimate the number of work-related training courses. It is found that women undertake significantly fewer training courses than men. Further, younger workers engage in training more frequently, as do higher the educated workers.

Table 1 contains the frequency distribution of the number of training courses taken during the period 1992-1996 in our data set. The figures illustrate the gradual increase in training participation in the Netherlands. In the period 1992-1994 67% of the workers participated in training, while during 1994-1996 nearly 72% participated in at least one training course. Further the share of workers who took seven or more courses in two years time nearly tripled. The share of workers with 4-6 courses increased as well, while the share of workers with 1-3 courses declined.

In Table 2 we calculated the average number of training courses taken by various sub-groups in the employed population for the periods 1992-1994 and 1994-1996. Compared to the 1992-1994 period, workers on average received 0.7 more courses during the period 1994-1996. In the latter two year period the average number of courses received was 2.7. Table 2 further shows that for all age, education and gender groups distinguished, the average number of training courses increased during the period under consideration. The figures further suggest that workers aged below 30 receive fewer courses than workers of older age groups. The same holds for the lowest and the highest educated workers. Finally, women receive fewer training courses than men, on average.



## 4 Estimation results

One assumption on which the ordered probit method is based is that the covariance between two observations is zero. With longitudinal data - as used in this paper - this amounts to the assumption that the error term of the unit of analysis (i.e. individual workers) is assumed to be uncorrelated over time. If they are, the effect of clustering on the training frequency is assumed to be similar for all individuals. In reality, however, the training frequency of individual workers may be correlated over time. With a positive inter-temporal correlation in training frequency, workers with a low (high) training frequency in one year have a low (high) training frequency in the next year as well. This positive inter-temporal correlation may affect training opportunities for workers. The findings in Table 3 seem to confirm this. It shows that for more than 75% of the workers the number of training courses taken between 1992 and 1994 equaled the number of training courses received in the period 1994-1996. For less than 25% of the workers the training frequency either increased or decreased over time. This suggests that there is a strong positive inter-temporal correlation in training.

To determine the existence of an inter-temporal correlation in training, a random effect ordered probit equation was estimated with only an intercept term and no explanatory variables. In addition to the examination of the existence of time dependency, this enables us to estimate to what extent the variance in individual training frequency can be attributed to human capital and firm related variables and to what extent it can be ascribed to individual specific effects. The intra-cluster (i.e. inter-temporal) correlation enables us to decompose the variance of the model into two elements: one of the time varying level (i.e. variation within individuals accross time)

and one of the individual level (i.e. between individuals). The results in Table 3 indicate that roughly speaking the *within* subjects correlation is 0.89 while the *between* subjects correlation is 0.11.

From the estimates for the entire sample of workers it appears that the inter-temporal correlation in training is high. It might be asked whether this findings holds for all sub-groups among workers. To analyze this we repeat this exercise for different age, education and gender groups in our sample. In all sub-samples distinguished the inter-temporal or within subjects correlation in training frequency was close to 90%. Furthermore, in nearly all sub-samples the percentage of workers receiving the same amount of training courses during 1992-1994 as in the period 1994-1996 was 60% or more.

Table 4 contains the parameter estimates of the (random effects) ordered probit equations on training frequency. To reduce the computational burden in the regression analysis we converted the education levels into a single variable >years of education=. The explanatory variables in the ordered probit equations include both human capital and other individuals characteristics, and job and firm related variables. The human capital and individual characteristics are: years of education, age, years of tenure at current job, gender, marital status, and hours of work. The job and firm characteristics are: eight dummy variables for industry, job level and firm size. It might be argued that it is more appropriate to estimate the equations for men and women separately. However, this would not allow us to test whether the coefficient of the gender variable is a random effect in our equations. For that reason we have chosen to estimate the model on a combined sample.

We limit the presentation of the coefficients to the variables of most interest, i.e.

age, education, gender and a time trend variable. We experimented with different specifications for the education and age variables. A specification with age, years of education and years of education squared proved the best fit for the data.

Training frequency is inverse U-shaped in years of education. The top of the parabola is around 12 years of education. This corresponds with an intermediate or upper-secondary level of education. Workers with only primary education and workers with a higher vocational or university education invest less in training than workers with an intermediate education level.

Somewhat surprisingly the age effect on training frequency is positive, indicating that older workers take part in more training courses than younger workers. In the equation we control for years of tenure at the current firm, however. The tenure effect on training is strongly negative.

Only in the random effects estimates we find a statistically significant effect of gender on training. In the random effects equations the training frequency for male workers is higher than for female workers.

As was already apparent from Table 1 and 2, there is a positive time trend in the training frequency. This is corroborated by the significantly positive effect of the time trend variable in the ordered probit regression. Compared to the period 1992-1994 workers in general took more courses during the period 1994-1996.

If we compare the results of the standard ordered probit equation with the random effects estimates in column 2, we find that the likelihood decreases dramatically compared with that in column 1. This indicates that the intercept should be considered as a varying coefficient. That is, training frequency varies over time and there is a time specific component to individual training frequency.

We also tested whether the coefficient of the age variable in our model could be considered as random effects varying over time, and whether this affects the results of the analysis. Regarding the latter, we find that treating parameters as random increases the size of the other coefficients in absolute size. According to Snijders & Bosker (1999, p. 228) this is known in the biostatistical literature as the phenomenon that the population-averaged effects (i.e. effects in models without random effects) are closer to zero than cluster-specific effects (which are the effects in models with random effects).

The estimation results in column 3 of Table 4 show that age should be treated as a random coefficient. Including age as a random parameter changes the loglikelihood from -5374.67 to - 5240.71.

Next we tested whether the education coefficient is a random effect. Treating the education coefficients as random effects reduces the loglikelihood from -5240.17 to - 5211.53. As this exceeds the critical value of the Chi-square distribution with two degrees of freedom, we may conclude that education is a random variable in our model as well.

Finally, the gender effect should also be treated as a random coefficient. If we include gender as a random variable the loglikelihood decreases from 5240.71 to 5206.59. Men are in general more likely to receive training than women, but some men and women are more likely to receive training than others.

A limitation of the ordered probit equation is that we have to specify a cut-off point. In the analysis we have used seven or more training courses as a cut-off. To test the robustness of the ordered probit results to this cut-off, we estimated some poisson regression equations on the total number of training courses taken. The summary of the

parameter estimates in the Appendix shows that the poisson regression estimates are comparable to the ordered regression coefficients. This strengthens our believe in the robustness of our finding to the type of model fitted to the data.

## 5 Conclusion

Two conclusions can be drawn from the analysis in this paper. The first is that we have found evidence to suggest that some workers are on a training track. There is a considerable consistency in training frequency among workers over time. More than three quarter of all workers received the same number of training courses during the period 1994-1996 as during the two years preceding 1994. This not only indicates that workers who received some training during the first period are likely to receive training during the next period as well, it also implies that workers who now do not participate in training are not likely to receive training in the future as well. Further, there is high inter-temporal correlation in training frequency. The inter-temporal correlation in training is about 0.9. This indicates that the within worker correlation over time is roughly 0.9.

The second conclusion is that individual characteristics such as education, age and gender should be treated as random effects, i.e. these characteristics have a varying impact on training frequency. This suggests that not all workers with the same education, age and gender receive the same amount of training, but that some of them receive more training than others.

A policy aimed at increasing training for workers is likely to benefit some workers more than others. The high inter-temporal correlation in training frequency combined with the high incidence of workers who receive no or only a small number of training courses over a two year period, suggests that a sizeable fraction of the work force is unlikely to benefit from a policy aimed at increasing the intensity of firm-related training. Furthermore, even among workers with characteristics that increase the likelihood of receiving training there are persistent differences in the number of training courses

received.

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**Table 1 Frequency distribution number of training courses taken during past two years by period**

	<i>1992-1994</i>	<i>1994-1996</i>
none	33.0%	28.2%
1	20.5%	15.6%
2	14.5%	13.7%
3	12.0%	11.5%
4	7.4%	8.7%
5	5.0%	8.0%
6	4.5%	5.2%
7 or more	3.1%	9.1%

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**Table 2 Average number of training courses taken for different sub samples during the period 1992-1994 and 1994-1996**

	<i>1992-1994</i>	<i>1994-1996</i>
All Workers	2.06	2.76
<i>Workers by age group</i>		
< 30 years	1.29	1.92
30 - 39 years	2.31	3.12
40 - 49 years	2.27	2.95
50 > years	2.20	2.75
<i>Workers by education level</i>		
Primary education	1.37	1.74
Lower vocational education	1.63	2.21
Lower general education	2.39	3.19
Intermediate vocational education	2.31	3.08
Secondary general education	2.76	3.75
Upper general education	2.46	3.55
Higher vocational education	2.58	3.51
University	1.96	2.89
<i>Workers by gender</i>		
Male	2.25	3.07
Female	1.74	2.27

**Table 3 Estimates (random effects) ordered probit for different sub samples (intercept term only, standard error of coefficient in brackets)**

	<i>Percentage non-varying responses over time</i>	<i>Parameter estimate intercept</i>	<i>Random effect variance term</i>	<i>Inter-temporal correlation</i>
All Workers		0.506** (0.021)	0	0
All Workers	75.5%	2.071** (0.063)	2.788	0.886
<hr/>				
<i>Workers by age group</i>				
< 30 years	76.9%	-0.002 (0.228)	3.049	0.903
30 - 39 years	72.6%	2.227** (0.131)	2.739	0.882
40 - 49 years	75.7%	2.414** (0.143)	2.838	0.890
50 > years	79.3%	2.775** (0.264)	3.254	0.914
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<i>Workers by education level</i>				
Primary education	87.6%	0.026 (0.539)	3.777	0.935
Lower vocational education	79.9%	0.179 (0.294)	3.569	0.927
Lower general education	77.4%	3.070** (0.296)	3.198	0.911
Intermediate vocational education	74.5%	2.238** (0.165)	2.744	0.883
Secondary general education	57.8%	2.674** (0.426)	2.197	0.828
Upper general education	71.2%	2.369** (0.407)	2.904	0.894
Higher vocational education	69.4%	2.196** (0.198)	2.569	0.868
University	79.8%	1.402** (0.218)	2.728	0.882

*Workers by gender*

Male	73.6%	2.121** (0.085)	2.724	0.881
Female	78.7%	1.933** (0.090)	2.850	0.890

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\* significant at 5% level; \*\* significant at 1% level.

**Table 4 Summary of parameter estimates random effects ordered response model (standard error of coefficient in brackets)**

	<i>ordered probit model</i>	<i>random effects ordered probit model</i>			
Intercept	-3.532** (0.264)	-7.323** (0.459)	-12.086** (0.911)	-10.774** (1.372)	-9.839** (1.101)
Age	0.013** (0.002)	0.047** (0.004)	0.102** (0.009)	0.084** (0.015)	0.073** (0.011)
Years of education	0.349** (0.039)	0.737** (0.066)	1.150** (0.138)	1.110** (0.211)	1.035** (0.168)
Years of education <sup>2</sup>	-0.015** (0.002)	-0.029** (0.003)	-0.043** (0.006)	-0.042** (0.010)	-0.038** (0.008)
Male	-0.027 (0.047)	0.292** (0.082)	0.841** (0.167)	0.779** (0.276)	0.813** (0.237)
Time trend	0.395** (0.064)	0.931** (0.109)	1.234** (0.123)	1.339** (0.134)	1.225** (0.128)
$\sigma_{\text{intercept}}$		3.049	2.497	4.624	4.530
$\sigma_{\text{age}}$			0.109	0.054	0.049
$\sigma_{\text{years of education}}$				0.116	
$\sigma_{\text{years of education squared}}$				0.007	
$\sigma_{\text{male}}$					2.243
Loglikelihood	-6701.213	-5374.671	-5240.712	-5211.530	-5206.592

Other control variables include: eight dummies for industry, firm size, marital status, years of tenure at the current firm, job level and hours of work; \* significant at 5% level; \*\* significant at 1% level.

**Appendix Summary of parameter estimates poisson regression on number of training courses taken (standard error of coefficient in brackets)**

	<i>Poisson</i>	<i>Poisson with random effect</i>
Intercept	-3.182** (0.178)	-4.395** (0.139)
Age	0.011** (0.001)	0.018** (0.001)
Years of education	0.337** (0.026)	0.426** (0.002)
Years of education <sup>2</sup>	-0.014** (0.001)	-0.017** (0.001)
Male	0.028 (0.029)	0.163** (0.022)
Time trend	0.434** (0.038)	0.334** (0.035)
$\sigma_{\text{intercept}}$		1.031
Loglikelihood	-8741.954	-6472.809

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Other control variables include: eight dummies for industry, firm size, marital status, years of tenure at the current firm, job level and hours of work; \* significant at 5% level; \*\* significant at 1% level.