THE INCIDENCE OF ON-THE-JOB TRAINING

An Empirical Study using Swedish Data

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Abstract: Using Swedish micro data, this paper examines the determinants of the incidence of, and the amount of, job-related training. The analysis is performed by estimating probit, count data and hurdle models with a set of explanatory variables chosen on a theoretical basis. The results show that the determinants of the probability of receiving training and the determinants of the amount of training not are the same.

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1 Introduction

Formal on-the-job training plays an important role in improving the skills of those in the labour force. According to Statistics Sweden, who investigate the size of employer-provided training, slightly less than 3 per cent of the GDP is used for training employees and approximately 40 per cent of all employed undertake some kind of job-related training every six months (Statistics Sweden, 1999). Data from Statistics Sweden (1992, 1995) also show that there are substantial differences in the incidence of on-the-job training between groups in the labour market. For example, on-the-job training seems to be most common among the middle-aged, workers in the public sector, and among individuals who work full-time. Moreover, women receive less training on average than men.

SOU (1991) stresses the importance of training as a complement to schooling, but also points out that training at the job increases the existing individual differences in educational background if those who are already well-educated get more training on average than those with shorter school education.

However, the information above is based on the uncontrolled means and it is of interest to see if the patterns appearing in these means are also true when covariates are controlled for. Several studies have shown that on-the-job training has a positive effect on wages, see e.g. Lynch (1992) who uses US data. Also Regnér (1995, 1997), using Swedish data, has shown that on-the-job training impacts on wage levels. Consequently, for several reasons it is of great interest to know who receives on-the-job training and who does not. Few studies have paid attention to the factors that determine the incidence of on-the-job training, i.e. who receives on-the-job training and who does not. Although there are studies that investigate the probability of receiving on-the-job training, or the issue of job-matching and on-the-job training, or both, no comparable Swedish study that examines the probability of receiving on-the-job training has been found.

Barron, Black and Loewenstein (1989) go into the matter of job-matching and on-the-job training using US survey data. Their results show that on-the-job training is uncorrelated with starting wages and they claim that the incidence of on-the-job training depends on selection of high-ability workers to positions where training is substantial.

Booth (1991) examines the probability of receiving job-related formal training and the returns to on-the-job training in Britain using a sample containing personal, educational and firm characteristics and by performing logit estimations. A positive relationship between education and on-the-job training is found as are negative relationships between age and training and private sector and training. The results also indicate large gender differences. Performing separate estimations for men and women shows that women are, on average and conditional on covariates, less likely than men to receive on-the-job training. The training incidence is also shown to have a large impact on earnings.

Arulampalam & Booth (1997) have examined the probability of receiving training using a British data set and modelling the number of training occurrences with the purpose of finding out why there are individual differences in the probability of receiving training, to what extent ability and education contribute to repeated occurrences of work-related training, and if there are any gender differences. The results show that education is important for obtaining on-the-job training and significant gender differences are found. Moreover they find that members of trade unions are more likely to take part in on-the-job training than non-members. A second goal is to investigate whether there is any evidence of a low skill, bad job trap in Britain. Strong complementarity between education and training is found and they come to the conclusion that this trap does exist to some extent.

The same results about education and gender are also found in a recent study by Goux & Maurin (2000) using French data. Their results also support the suggested positive relationship between firm size and training and show that the individual's position within the firm seems to be important for the incidence of on-the-job training. Their conclusion is that on-the-job training is more common if you are at a higher level in the hierarchy.

The purpose of this paper is to obtain an understanding of which factors determine whether an individual receives on-the-job training or not and the amount of training received. Three kinds of estimation methods will be used on Swedish micro data from 1991. To see what determines the incidence of on-the-job training, a probit model is estimated. The determinants of the amount of training received is then estimated with a count data model, since the number of on-the-job training days is a variable that takes only non-negative integer values. Finally, the suggestion that there are two separate mechanisms affecting the on-the-job training incidence and the number of training days will be evaluated by using a hurdle specification.

The paper is organised as follows. The next section deals with theory concerning on-the-job training. In the third section the data is presented and in the fourth section, the estimation methods and the results from the estimations are discussed. Finally, the fifth section summarises and concludes with the main results of the study.

2 The theoretical framework

Human capital theory will be the basis for the forthcoming analysis (see Becker, 1964), but other theories will also be used in order to attempt to discover which factors that are theoretically likely to affect the probability of receiving formal on-the-job training.

According to human capital theory, agents will invest in training if the discounted net present value of training benefits exceeds training costs. For the individual, the decision to take part in training is made on expectations about the costs for training, i.e. no or lower wages during the training period, and about the benefits in terms of higher wages after training. For the employer, the decision is made on expectations about the benefits in the form of raised post-training productivity and the costs for lost productivity during the training period and perhaps also costs for the training itself.

In the case of general training, if the company pays for the training and the worker later leaves the company, the company will lose the returns to the investment. The worker on the other hand, will be willing to pay since he can use his general knowledge in other companies. Consequently the costs for general training will be born by the worker. In the case of specific training, the worker's alternative wage is not altered and hence, he will not be willing to pay the full price for the training since the returns will be lost in case of a lay-off. The employer will not be willing to pay either since he loses if the worker quits. The solution is that the worker and the employer share the costs for specific training, a solution that also provides an incentive for the worker to stay at the company and for the company to keep the worker, i.e. it increases tenure and reduces turn-over.

In the case of employer-provided training the above reasoning implies that the incidence of on-the-job training can be assumed to depend both on the employer as well as the employee. The individual's cost for on-the-job training consists theoretically, as mentioned before, of lower wages during the training period. On the other hand, future wages have to be higher since otherwise no worker would be willing to invest in training. This means that compared to occupations with no on-the-job training, occupations that contain on-the-job training will have lower starting wages. After the training period, the wage will increase and will eventually exceed the wage for occupations with no on-the-job training. Nevertheless, a positive relationship between wages and on-the-job training is also possible. If marginal taxes are high, on-the-job training can be a valuable, non-pecuniary compensation that is more appreciated by the employee than a pecuniary compensation, see e.g. Granqvist (1998) for an examination of fringe benefits.

Since the employer wants to maximise his returns on the investment in on-the-job training, i.e. raise production as much as possible, part-time workers can be assumed to have a smaller probability of receiving on-the-job training. Also workers who are perceived to have higher turn-over rates should be less likely than other workers to receive employer-provided training. For the same reason gender differences in employer-provided training are possible. If, on average, women are more likely to be absent from work, for example due to greater family responsibilities, the employer's incentives for investing in training will be lower for women than for men. There is also a possibility that on-the-job training can be used as a tool for discrimination.

Another implication of human capital theory is that individuals who learn quickly, i.e. the ones with the highest ability who have a low cost for learning, would be more likely to take part in training since they are associated with lower costs for training. It is likely that these quick learners are the same individuals who have also invested in higher education and hence, formal education is expected to be positively correlated with on-the-job training. Still, it should be taken into consideration that some ability bias probably affects the estimated effect of education and therefore the effects of education may be overestimated (for an examination of ability bias using Swedish data see e.g. Kjellström, 1999). Since human capital theory suggests that both formal education and on-the-job training should take place when the individual is young so that the return on the investment can be recouped over a longer time period, age and training are likely to be negatively correlated.

An alternative to human capital theory is the argument of screening. According to this theory, employers compensate the lack of information about an individual's true capacity by using the individual's formal education, i.e. schooling, as a screening device to sort out those with the highest ability. In the case of training, rational employers use former school education as a screening device to detect the most suitable for training, i.e. those who are quick learners and hence have a lower cost for learning. Employees in their turn will use their education as a signal of their productivity.

Due to the concept of complementary effects, individuals with a greater capacity to learn probably acquire larger stocks of both general and specific human capital. Oi (1983, pp.72-73) argues that the firms will gain from hiring more able workers since their general human capital will have a complementary effect on the productivity of specific human capital.

To sum up, both these arguments support the positive relationship between school education and training that was suggested by human capital theory, but on other grounds.

The size of the company where the individual is working is most likely to affect the probability of receiving on-the-job training. Larger companies may have lower training costs per employee than smaller firms because they can spread fixed costs for training over a large group of employees. The production loss of having one additional worker in training is probably also lower for larger firms.

The labour market sectors are also likely to affect the probability. It is reasonable to think that if private sector firms are more constrained by the need to make profits than public sector firms, which probably is the case, then private sector firms will be less willing to finance training than public sector firms, see Booth (1991). Therefore, compared to working in the public sector, working in the private sector might have a negative impact on the probability of receiving training.

Besides sector, there are an institutional factor that might influence the incidence of on-the-job training namely the power of unions. In union establishments, employer incentives to provide training could be low due to high wages. If minimum wages are high, employers might not be able to afford to provide training since the necessary lowering of wages during the training period is not allowed. On the other hand, unions want to improve the situation of their members. Arulampalam & Booth (1997) argue that unions might be co-operative and thereby increase training and productivity. Also, unions might be able to increase both wages and training through negotiation. Consequently, the impact of belonging to a union can be either negative or positive.

Now again consider the impact of education. A positive relationship between education and training has been suggested, but what happens to those who have poor educations? Burdett & Smith (1995) have shown that if there is a high proportion of uneducated workers, firms' incentives to provide jobs requiring training will be small and if there are few good jobs, workers may have little incentive to obtain higher skills. This results in a skills-segmented labour market where some individuals will get caught in low productivity with small chances to receive on-the-job training and consequently smaller chances for good performance on the labour market. They are said to get caught in a low skill, bad job trap. Complementarity between education and on-the-job training, i.e. if education and on-the-job training are positively correlated, is an indication of the existence of a bad job trap.

The largest association of trade unions in Sweden – LO – (represents the blue-collar workers) conducts surveys to describe the working situation of their members and non-members in terms of freedom in work, chances for on-the-job training etc. (see Landsorganisationen i Sverige, 1999). The survey referred to here shows that, on average, employees in higher paying jobs have more freedom in their work. For example, they can decide their own working methods to a greater extent, they have flexible working hours, they receive more on-the-job training and they have altogether a greater influence on their working situation, while low-paid workers do not have the same opportunities. If the labour market is segmented, it is likely that individuals with more freedom in work are more likely to receive on-the-job training since they work in areas where on-the-job training is substantial. Hence, some workplace characteristics describing the individual's working situation can be supposed to be correlated to the probability of receiving training.

3 Data

The data that has been used is from the Swedish Level of Living Survey 1991. The complete database contains information about a random sample of approximately 6,000 people between the ages of 18-75 (for more details see Fritzell & Lundberg, 1994). This study focuses on employed individuals aged 18-64, except for self-employed and farmers who have been excluded since they are considered to work under other conditions than the rest of the population. Only the respondents who have answered all of the relevant questions are included. After these limitations, the sample consists of slightly less than 3,000 individuals.

Two different dependent variables will be used in the following estimations. The first dependent variable takes the value one if the individual received any formal on-the-job training during the past twelve months before the interview and zero otherwise. The second dependent variable is discrete and measures the number of days of on-the-job training received during the last twelve months. The explanatory variables have been chosen on basis of the theoretical explanations and their following implications together with the experiences from the studies mentioned in the introduction. The variables used, their definitions and mean characteristics can be seen in Table 1.

As can be seen from Table 1, there are three kinds of individual characteristics, namely gender, age and education level.[1] Other variables used are firm size, part-time working,

[1] The education levels correspond to the following Swedish terms: *folkskola, real- eller grundskola, studentexamen* and *akademisk examen*. For further information about the education levels, see SOFI (1998).

Table 1. Definitions and mean characteristics

Variable	Definition	Mean (standard deviation)		
		All	Men	Women
Dependent variable 1	1 if on-the-job training during the last 12 months	0.444	0.473	0.413
Dependent variable 2	No. of on-the-job training days during the last twelve months	4.7 (14.2)	5.4 (15.6)	3.9 (12.5)
Woman	1 if woman	0.488	0	1
Age	Age in years	39.9 (12.2)	40.1 (12.1)	39.8 (12.2)
Elementary school	1 if highest education level is elementary school	0.248	0.260	0.235
Lower school certificate	1 if highest education level is lower school certificate	0.468	0.441	0.498
Completed high school	1 if highest education level is completed high school	0.187	0.187	0.187
Academic degree	1 if highest education level is academic degree	0.097	0.112	0.080
Part-time	1 if working < 35 hours/week	0.224	0.067	0.389
Small firm	1 if working in a small firm (≤19 employees)	0.306	0.271	0.343
Middle-size firm	1 if working in a middle-size firm (20-99 employees)	0.524	0.548	0.500
Large firm	1 if working in a large firm (≥100 employees)	0.170	0.181	0.157
Blue-collar, unskilled	1 if individual belongs to this occupational group	0.301	0.255	0.348
Blue-collar, skilled	As above	0.194	0.269	0.115
White-collar, unqualified	As above	0.072	0.033	0.113
White-collar, low-level	As above	0.108	0.079	0.139
White-collar, middle-level	As above	0.183	0.175	0.192
White-collar, high-level	As above	0.142	0.189	0.093
Union member	1 if union member	0.835	0.837	0.832
Private sector	1 if working in private sector	0.556	0.705	0.400
Municipal sector	1 if working in municipal sector	0.314	0.156	0.479
Governmental sector	1 if working in governmental sector	0.130	0.139	0.121
Learning-time	1 if the time to learn to perform the job reasonably well is >3 months	0.603	0.734	0.465
Decision-maker	1 if decision-maker at work	0.461	0.504	0.416
New knowledge	1 if acquiring new knowledge at work	0.484	0.517	0.449
Number of observations		2961	1517	1444

Note: Table 3 shows the frequency distribution for the number of training days.

occupational group, sector, union membership and some indicators of the workplace. These three workplace characteristics are used as a measure of the individual's working situation. The first one called "Learning-time" can be seen as an indicator of a low skill or high skill job. The second, called "Decision-maker", measures the individual's responsibilities and the third one, "New knowledge", is used as an indicator of the individual's opportunities to progress. They are all likely to be positively correlated with on-the-job training.[2]

The public sector is divided into two parts, governmental and municipal. There are two reasons for this. First, the governmental and the municipal sector have been shown to differ to some extent in the returns to human capital (e.g. Zetterberg, 1994). Second, data from Statistics Sweden (1992, 1995) show that on-the-job training is more common in the governmental sector than in the municipal sector. It might therefore be interesting to see whether these two parts of the public sector also differ here. The occupational groups are based on the Socio-Economic Classification (*Socio-ekonomisk indelning, SEI)*, which is a vertical classification.[3]

According to the theoretical framework in Section 2, starting wages are supposed to be negatively correlated with on-the-job training. However, this requires a measure of starting wages, which is not available here. Also, since on-the-job training generally is expected to cause wage increases and not the other way around, it seems reasonable not to include a wage variable.[4] Besides education, no measure for ability is available.

Variables that have been tried out but then excluded are working experience and tenure. Working experience was used instead of age but came out insignificant in all estimations. Also tenure has been shown not to affect either the incidence or the amount of training in these models. Just as for wages, there is a causality problem concerning tenure since on-the-job training generally is suggested to increase tenure, though the reverse relationship would be possible if employers reward long time employees.[5]

[2] The workplace characteristics used here are just a few examples of the autonomy variables available. The data set also contains variables describing the individual's working environment in terms of noise, stress, physical and mental efforts etc. that have been experimented with but not are used in the final estimations since they seldom are significant.
[3] See SOFI (1998) for a further description of *SEI*. For the first occupational group, the *SEI* codes 11 and 12 are used, for the second the codes 21 and 22, for the third code 33, for the fourth codes 35 and 36, for the fifth codes 45 and 46 and for the sixth group codes 56 and 57 are used.
[4] Barron *et al.* (1989) also argues that the relationship between training and the starting wage is ambiguous.
[5] To test the effect of tenure in another way, separate estimations for one group with up to 2 years of tenure and one with more than 2 years tenure have been performed. The estimates are very similar to the ones for the whole sample.

4 Empirical analysis

4.1 Probit Estimation

Assume there is a latent variable d_i^* describing individual i:s desire to participate in at least one on-the-job training course. We define

$$d_i^* = X_i'\beta + \varepsilon_i \tag{1}$$

where X_i' is a vector of explanatory variables with the associated β vector and ε_i is an error term. What is observed here is a dummy variable defined as

$$d_i = \begin{cases} 1 & if\ d_i^* > 0 \\ 0 & otherwise\ . \end{cases} \tag{2}$$

Hence, the model estimated has a binary dependent variable d_i that consists of two possible outcomes and the observed d_i are realisations of a binomial process with a probability that varies from trial to trial depending on the set of explanatory variables.

The likelihood function is given by

$$L = \prod_{d_i=1} P_i \prod_{d_i=0} \left(1 - P_i\right) \tag{3}$$

where P is the probability of receiving on-the-job training. The estimation method used is probit (see e.g. Greene, 1997) where the estimations are undertaken by maximum likelihood. Both the estimated coefficients and the marginal effects are presented. The marginal effects are evaluated at the means of the regressors and estimate the change in probability due to a unit change in the regressor, *ceteris paribus*. For dummy variables, the marginal effect estimates the change in probability for the discrete change in the dummy from zero to one.

The results from the probit estimation can be seen in Table 2. Considering the individual characteristics, the gender effect is not significant and education level does not seem to have as strong an impact as could be expected from theory. However, one education

Table 2. Estimated coefficients and marginal effects from probit estimation. The dependent variable takes the value one if the individual has received formal on-the-job training during the last twelve months and zero otherwise. Robust standard errors within parentheses

Variable	Coefficient	Marginal effect
Constant	-2.021 (0.287) **	…
Individual characteristics		
Woman	-0.051 (0.058)	-0.020 (0.023)
Age	0.044 (0.014) **	0.017 (0.006) **
Age^2 /100	-0.056 (0.017) **	-0.022 (0.007) **
Elementary school	Ref.	Ref.
Lower school certificate	0.083 (0.071)	0.033 (0.028)
Completed high school	0.257 (0.092) **	0.102 (0.037) **
Academic degree	-0.084 (0.121)	-0.033 (0.047)
Employment characteristics		
Small firm	Ref.	Ref.
Middle-size firm	0.188 (0.057) **	0.074 (0.022) **
Large firm	0.243 (0.076) **	0.096 (0.030) **
Part-time	-0.133 (0.066) *	-0.052 (0.026) *
Blue-collar, unskilled	Ref.	Ref.
Blue-collar, skilled	-0.013 (0.075)	-0.005 (0.030)
White-collar, unqualified	0.241 (0.102) *	0.096 (0.041) *
White-collar, low-level	0.355 (0.093) **	0.141 (0.036) **
White-collar, middle-level	0.347 (0.085) **	0.138 (0.034) **
White-collar, high-level	0.410 (0.111) **	0.162 (0.047) **
Institutional factors		
Private sector	Ref.	Ref.
Municipal sector	0.106 (0.061)	0.042 (0.025)
Governmental sector	0.199 (0.078) *	0.079 (0.030) *
Union member	0.353 (0.071) **	0.135 (0.026) **
Workplace characteristics		
Learning-time	0.251 (0.059) **	0.098 (0.023) **
Decision-maker	0.247 (0.055) **	0.097 (0.021) **
New knowledge	0.222 (0.052) **	0.087 (0.020) **
Number of observations	2961	2961

** significant at 1% level
* significant at 5% level

effect is significant; the probability of receiving on-the-job training is about 10 per cent higher if the individual has completed high school compared to having completed elementary school only, which is the reference group. These first two findings will be discussed further.

According to theory, a negative correlation between age and training is expected. Experimenting with a linear term only, did not give any significant result so a quadratic relationship was tried out and here both coefficients are significant at the one per cent level. Consequently, the probability of receiving on-the-job training increases with age until a maximum point is reached, and then the probability decreases.[6] This estimated relationship between age and training seems reasonable. First, younger workers may have a higher job mobility and the risk associated with the investment in training is therefore higher, second they might not need as much education as older people since they already have the right knowledge and third, training can be used as a reward for those who have been employed for a longer time period. The oldest workers receive less training than the middle-aged since the returns to the investment are very low close to retirement.

The size of the company seems to have the effect that was suggested by theory, i.e. larger companies more often offer on-the-job training. This result is consistent with the findings from the French data used by Goux & Maurin (2000) and Booth (1991) on British data. Compared to working in a small firm, working in a middle-size firm leads to a 7 per cent higher probability of receiving training and working in a large firm leads to a 10 per cent higher probability. The result for part-time workers is also the expected. The probability of receiving on-the-job training is about 5 per cent lower for those working part-time compared to those working full-time.

The estimated coefficients of the variables indicating occupational group are all significant with positive signs for the white-collar workers compared to unskilled blue-collar workers while the effect of skilled blue-collar workers is insignificant. Unqualified white-collar workers have an on-the-job training probability that is about 10 per cent higher than the reference while the following two levels of white-collar workers have around 14 per cent higher probability. The highest level of occupation, high-level white-collar worker, has a probability that is around 16 per cent higher than the reference. The marginal effects for the occupational groups are, compared to the estimated effects of other variables, rather large and

[6] The maximum point is calculated to be about 39 years.

hence have a greater impact on the on-the-job training incidence than those of for example firm size or part-time working.

Now consider the institutional factors. Working in the governmental sector brings about a probability of receiving training that is close to 8 per cent higher than if working in the private sector. The effect of working in the municipal sector is also positive but not significant at the lower levels.[7] To some extent, this supports the suggestion that private firms are more restrictive in offering on-the-job training to their employees, perhaps because they are more constrained by the need to make profits. Union members have almost 14 per cent higher probability than non-members, a result that might support the theory about the monopoly power of unions and is consistent with the results of Booth (1991).

Next consider the variables under the heading workplace characteristics where all the estimated effects are clearly significant. If the time to learn to perform the job reasonably well is greater than three months, the probability is slightly less than 10 per cent higher than otherwise. The decision-maker variable shows the same result and if you acquire new knowledge at work, you have a 9 per cent higher probability .

To sum up, in most cases the results are the expected. It is a bit surprising though that there seems to be a lack of the complementarity between education and training that was found by Booth (1991) and Arulampalam & Booth (1997). A possible explanation could be that the occupational groups, that are likely to be positively correlated with the educational levels, absorb the education effect. However, if the occupational groups are excluded, the highest education level, academic degree, will still be insignificant although the other education levels are significant compared to the reference. For the academic group, it is likely that the training is less formal and is integrated in the daily work instead.

Another result that is of great interest is that the estimated gender effect is not significant at any conventional level which means that according to this model, there is no effect of being a woman instead of a man, in contrast to the results by Arulampalam & Booth (1997), Booth (1991) and Goux & Maurin (2000) where considerable gender differences were found. To further test for potential gender differences, interaction variables have been used. All variables have been interacted with the gender variable. Only the interaction variables for woman and the two levels of company size are significant at the 5 per cent level. The marginal effects are remarkably large with negative signs implying that women in middle-size or large companies have a considerably lower probability of receiving on-the-job training than

[7] The estimated coefficient for the municipal sector is significant however at the 10 per cent level and is therefore interpreted with some caution.

men in the same type of company.[8] The age-interaction variables are not significant separately but they are jointly significant at the 5 per cent level.[9] Besides these findings, there are no other significant gender differences in the incidence of on-the-job training.

4.2 Estimation of a Count Data Model

To generate better understanding of the factors affecting the incidence of on-the-job training, it is interesting not just to estimate whether an individual receives training or not, but also the amount of on-the-job training, i.e. how many days of training he or she receives. The dependent variable used in the next part of estimations will be the number of on-the-job training days received during the last twelve months. As can be seen from the frequency distribution in Table 3, approximately 57 per cent of the sample have a zero count, i.e. they have not taken part in any formal on-the-job training during the last year.

Table 3. Frequency distribution of the number of days of on-the-job training received during the last twelve months

Number of on-the-job training days	Observed frequencies	Proportions
0	1682	56.8
1	101	3.4
2	162	5.5
3	144	4.9
4	110	3.7
5	237	8.0
6	44	1.5
7	63	2.1
8	38	1.3
9	10	0.3
10	131	4.4
11+	239	8.1
Total	2961	100

Note: The maximum number of days is 222.

Given the nature of the dependent variable, i.e. when it takes the form of non-negative integer values, a count data model can be used. For a more detailed examination of count data models than will be given here, see e.g. Winkelmann & Zimmermann (1995). A common starting-point for count data models is a Poisson model where the Poisson distribution provides the

[8] The estimated marginal effect of woman*middle-size firm is approximately -0.32 and of woman*large firm is about -0.56.

[9] For determining whether one single variable is significant in interaction, the p-value has been used. To test if groups of variables are jointly significant, i.e. all variables significantly not equal to zero, Wald tests have been performed. The Wald test statistic has a χ^2 distribution with one degree of freedom under the null hypotheses that all variables are jointly equal to zero, see e.g. Greene (1997).

probability of the number of event occurrences, in this case days of on-the-job training.[10] The probability of y number of occurrences for individual i is given by

$$P(Y_i = y_i) = \frac{e^{-\lambda_i} \lambda_i^{y_i}}{y_i!} \qquad y_i = 0, 1, 2, \ldots \tag{4}$$

where

$$E(Y_i) = Var(Y_i) = \lambda_i \; .$$

This statistical model is characterised by a single parameter implying the equality of the conditional mean and the conditional variance (equidispersion). There are two assumptions that need to be considered. First, individuals are only allowed to be heterogeneous with respect to the observed characteristics. Second, events must occur randomly over time. Violations of these assumptions might cause overdispersion, i.e. the conditional variance exceeds the conditional mean, a feature that is common in economic data.

Many zeros are a source of overdispersion. One way to try to find out whether the Poisson distribution is appropriate or not is to calculate the frequency of each count by using *Equation 4* with λ_i replaced by the sample mean and compare the results to the observed frequencies.[11] The calculation shows that if the data were Poisson distributed, there would not be as many zeros as observed. As Arulampalam & Booth (1997) argue, this overdispersion can depend on unobserved heterogeneity in the mean function or that the probability of receiving on-the-job training is increased as a result of past on-the-job training. Therefore, a model which allows for overdispersion needs to be specified.

A common generalisation of the Poisson model that allows for overdispersion is the negative binomial distribution (Winkelmann & Zimmermann, 1995). Here, unobserved heterogeneity is introduced in the model by using an error term assumed to have a gamma distribution, which leads to a negative binomial distribution for the number of occurrences. Formally, λ_i is specified as

$$\lambda_i = \exp\left(X_i^{'}\beta + \varepsilon_i\right) \tag{5}$$

[10] For an application of Poisson models, see e.g. Melkersson (1999).
[11] As can be seen from Table 1, the sample mean is 4.7 days of on-the-job training.

and the unobserved individual effects are thereby introduced in the conditional mean by the disturbance ε_i that reflects the cross-sectional heterogeneity. The negative binomial model hence arises from the introduction of unobserved heterogeneity into the Poisson model, so in negative binomial models, the count variable is believed to be generated by a Poisson-like process except that the variation is greater than that of a true Poisson. Following Winkelmann & Zimmermann (1995), the negative binomial distribution is given by

$$P(Y_i = y_i) = f(y_i | \alpha_i, \lambda_i) = \frac{\Gamma(\alpha_i + y_i)}{\Gamma(\alpha_i)\Gamma(y_i + 1)} \left(\frac{\alpha_i}{\lambda_i + \alpha_i} \right)^{\alpha_i} \left(\frac{\lambda_i}{\lambda_i + \alpha_i} \right)^{y_i} \qquad (6)$$

$$y_i = 0,1,2,\ldots$$

with

$$E(Y_i | \alpha_i, \lambda_i) = \lambda_i \qquad\qquad Var(Y_i | \alpha_i, \lambda_i) = \lambda_i + \alpha_i^{-1} \lambda_i^2 \;,$$

i.e. the expected value is the same as for the Poisson distribution, but the variance here depends both on λ and on α, which is the common parameter of the gamma distribution. Given that α is greater than zero, the variation will be greater than that of a true Poisson. By testing whether α is equal to zero or not, we can discriminate between the two models. Besides the estimated coefficients of the explanatory variables, an estimate of α is given by the estimation of a negative binomial model. A likelihood ratio test of the null hypothesis that α is equal to zero is rejected at the one per cent level and hence the negative binomial distribution is to be preferred, as was expected.

Table 4 shows the results from the estimation of a negative binomial model. Only the signs and the levels of significance are interpreted. The dependent variable measures, as already mentioned, the number of days of on-the-job training received the last twelve months. The explanatory variables used are the same as in the probit estimation and are defined in Table 1.

First, here is evidence for gender differences found because the effect of the gender dummy is now significant whereas in the probit estimation it was not. The negative sign implies that, according to this model and *ceteris paribus*, women receive fewer days of on-the-job training than men. The age variables have the same signs as in the former estimation and are both significant.

Table 4 Negative binomial estimation. The dependent variable is the number of on-the-job training days received during the last twelve months. Robust standard errors within parentheses

Variable	Coefficient
Constant	-0.657 (0.659)
Individual characteristics	
Woman	-0.221 (0.100) *
Age	0.064 (0.028) *
Age^2 /100	-0.098 (0.035) **
Elementary school	Ref.
Lower school certificate	0.359 (0.168) *
Completed high school	0.536 (0.201) **
Academic degree	0.123 (0.211)
Employment characteristics	
Small firm	Ref.
Middle-size firm	0.114 (0.127)
Large firm	0.551 (0.174) **
Part-time	-0.556 (0.148) **
Blue-collar, unskilled	Ref.
Blue-collar, skilled	-0.363 (0.181) *
White-collar, unqualified	-0.429 (0.197) *
White-collar, low-level	0.363 (0.198)
White-collar, middle-level	-0.045 (0.172)
White-collar, high-level	-0.031 (0.199)
Institutional factors	
Private sector	Ref.
Municipal sector	0.466 (0.130) **
Governmental sector	0.508 (0.120) **
Union member	0.442 (0.152) **
Workplace characteristics	
Learning-time	0.038 (0.126)
Decision-maker	0.364 (0.107) **
New knowledge	0.483 (0.105) **
Estimated α	4.692**
Number of observations	2961

** significant at 1% level
* significant at 5% level

Next consider the education levels. Here, the coefficients of the dummies for lower and completed high school are significant. The signs are positive and consequently individuals with a higher education (except for an academic degree) receive significantly more days of on-the-job training than individuals with only elementary school education.

The coefficient for “Large firm” is positive and significant here and should hence be assumed to affect the number of training days in a positive way, as was expected from theory and consistent with the result of the probit estimation. The coefficient for “Middle-size firm” is not significant. The part-time variable shows that working part-time instead of full-time clearly reduces the number of training days, just as it was shown to reduce the probability of receiving any training at all.

Moreover, only two of the effects of the occupational group variables are significant compared to the reference group. The signs are negative, which implies that skilled blue-collar workers and unqualified white-collar workers receive significantly less training days than unskilled blue-collar workers while the effects of the higher levels of white-collar workers are insignificant.

The effects of the two sector dummies are positive and significant. This implies that working in the municipal or governmental sector not only increases the probability of on-the-job training incidence compared to working in the private sector, but also the number of training days. The effect of being a union member is also clearly positive just as the effects of two of the workplace variables, the decision-maker variable and the new-knowledge variable.

To sum up, the estimation of a negative binomial model comes up with some results that are the same as from the probit estimation, while some results are different. An interesting result is that the gender dummy is significant here and hence indicates that given these covariates, the training days received are fewer for women than for men.[12] A second interesting finding is that the highest education level still is insignificant and hence does not support the idea that it is the most well educated who receive most training.

4.3 Estimation of a Hurdle Model

One limitation of the previously discussed models, is that the zeros as well as the positive counts are assumed to be generated by the same process since by using the probit or negative binomial approach, the process generating the zeros is modelled in the same way as the

[12] As in the probit estimation, interaction variables have been tried out. It is worth noting that the coefficients for two of the occupational group variables (unqualified white-collar and middle-level white-collar) are significant with negative signs in interaction with the gender dummy. No other coefficients are significant.

process generating the positive counts. In this sample, there are many zero counts since more than half of the individuals did not take part in any on-the-job training during the previous year. It is reasonable to think that these zeros are generated in a different way from the positive counts, implying that the individuals who receive training and those who do not systematically differ from each other. There might be one mechanism deciding whether an individual receives on-the-job training or not and another mechanism that rules the amount of training received when training is given.

Dividing the sample into two groups, one with those who have received on-the-job training and one with those who have not, and examining the means for each group gives some support for the above reasoning. For example, the individuals who received at least some on-the-job training last year have a higher level of education on average than those who had not received training. They also work to a greater extent in the governmental sector and to a lesser extent in the private sector, belong more often to the higher occupational groups, work to a greater extent in larger companies and a greater part are members of unions. This is consistent with the results from the estimated probit and negative binomial models. Also, the majority of this group are men, compared to the no-training group where the majority are women. The differences that have been pointed out give some evidence for the suspicion that there might be systematic differences among those individuals who receive on-the-job training and those who do not.

This might also imply that there are two separate mechanisms governing the incidence of on-the-job training and the amount of training. To take this into consideration, a hurdle model can be used. Here it is assumed that a binomial process governs the binary outcome of whether or not the individual gets any training and, once the hurdle is crossed, the conditional distribution of the positive values is governed by a truncated-at-zero count data model. The hurdle model hence consists of two steps. The first step involves estimating the probability of receiving on-the-job training. The second step estimates how many days of on-the-job training an individual receives given that he or she receives training, i.e. that the parameter in the first step takes the value one. In principle, the hurdle could be set at any value, but here only the hurdle-at-zero model is discussed.

Now, a hurdle model will be set up. To a great extent the presentation will follow that of Arulampalam & Booth (1997). First, let Y_i denote the number of on-the-job training days for individual i. Then let f_1 be the probability distribution function of the process governing the hurdle, i.e. the incidence of training, and let f_2 be the probability distribution function of the process governing the number of training days once the hurdle is crossed. The probability distribution of the variable Y_i is then given by

$$P(\text{no training}) = P(Y_i = 0) = f_{1i}(0) \tag{7}$$

$$P(y_i \text{ training days}) = P(Y_i = y_i) = f_{2i}(y_i)\left[1 - f_{1i}(0)\right] / \left[1 - f_{2i}(0)\right] \qquad y_i = 1,2,3,\ldots$$

and the likelihood function is given by

$$L = \prod_{y=0} f_1(0) \prod_{y>0}\left[1 - f_1(0)\right] \prod_{y>0}\left\{ f_2(y) / \left[1 - f_2(0)\right]\right\} . \tag{8}$$

The first two terms of the likelihood function refer to the likelihood for training incidence, while the third term is the likelihood for positive counts for the number of training days. Therefore, the likelihood is separable and the two steps can be estimated separately by first maximising the likelihood of a binary model and then maximising the likelihood of the truncated variable. For the first step, the probit approach has been chosen. For the second step, the strict application of a Poisson or negative binomial model cannot be used since the probability would not sum to one when the possibility of a count being equal to zero is excluded. Therefore, it is necessary to use an estimation method that truncates at zero. Here, the truncated negative binomial distribution is used to estimate the second step, i.e. estimate the effects on the number of training days given that training is received. As in the negative binomial model in the former part of estimations, the variance parameter a is estimated and is shown to be significantly different from zero.

The results from the estimated hurdle model can be seen in Table 5, where the probit estimation and the truncated-at-zero negative binomial estimation are presented together and the first and the second step can be compared. In order to avoid confusion no marginal effects are presented, only the estimated coefficients.

First consider the individual characteristics. The coefficient of the gender dummy is negative but not significant in the probit estimation and negative and significant in the second step. This implies that there are no gender differences in the incidence of on-the-job training but given that the hurdle is crossed, women receive less training than men do on average. There are some possible explanations for why women would receive less training than men. First, they might choose other occupations than men. Second, it might be less valuable for an

Table 5. Hurdle model. The first step (1) is estimated with probit and the second step (2) with truncated negative binomial. Robust standard errors within parentheses

Variable	(1) Training incidence	(2) Positive counts
Constant	-2.021 (0.287) **	2.281 (0.657)**
Individual characteristics		
Woman	-0.051 (0.058)	-0.217 (0.108) *
Age	0.044 (0.014) **	-0.036 (0.031)
Age^2 /100	-0.056 (0.017) **	-0.016 (0.035)
Elementary school	Ref.	Ref.
Lower school certificate	0.083 (0.071)	0.307 (0.151) *
Completed high school	0.257 (0.092) **	0.443 (0.192) *
Academic degree	-0.084 (0.121)	0.280 (0.208)
Employment characteristics		
Small firm	Ref.	Ref.
Middle-size firm	0.188 (0.057) **	0.024 (0.115)
Large firm	0.243 (0.076) **	0.274 (0.144)
Part-time	-0.133 (0.066) *	-0.521 (0.139) **
Blue-collar, unskilled	Ref.	Ref.
Blue-collar, skilled	-0.013 (0.075)	-0.460 (0.191) *
White-collar, unqualified	0.241 (0.102) *	-0.808 (0.229) **
White-collar, low-level	0.355 (0.093) **	-0.022 (0.206)
White-collar, middle-level	0.347 (0.085) **	-0.435 (0.185) *
White-collar, high-level	0.410 (0.111) **	-0.545 (0.210) **
Institutional factors		
Private sector	Ref.	Ref.
Municipal sector	0.106 (0.061)	0.288 (0.123) *
Governmental sector	0.199 (0.078) *	0.374 (0.121) **
Union member	0.353 (0.071) **	0.144 (0.132)
Workplace characteristics		
Learning-time	0.251 (0.059) **	-0.234 (0.133)
Decision-maker	0.247 (0.055) **	0.159 (0.107)
New knowledge	0.222 (0.052) **	0.302 (0.099) **
Estimated α	…	1.696 **
Number of observations	2961	1279

** significant at 1% level
* significant at 5% level

employer to invest in training for women if the returns on the investment are lower, e.g. because of more absence from work due to family responsibilities. Third, women might be discriminated.

The age variables only affect the incidence of on-the-job training and not the number of days conditional on incidence, while there are education effects in both steps. In the first step, only the third education level (completed high school) is significant but given that training is received, i.e. in step two, both a lower school certificate and completed high school have a positive impact on the days of training compared to the reference. Still, an academic degree does not seem to increase either the probability of receiving training or the amount of training.

The variables under the heading employment characteristics show that the firm size has a positive influence on the incidence the number of days but no significant effect on them. The part-time variable however is significant with a negative sign in both steps. Working part-time reduces both the probability of receiving on-the-job training and the number of training days when training is given.

The coefficients of the occupational groups differ remarkably between the first and the second step. Compared to the reference group, unskilled blue-collar workers, the probability of receiving training is significantly higher for all the other groups except skilled blue-collar workers. Conditional on incidence however, the effect on the number of training days is significant and negative for skilled blue-collar workers and unqualified, middle-level and high-level white-collar workers. For these groups, the amount of training conditional on incidence is consequently lower than for the reference group.

Next consider the sector variables. The results show that individuals in the public sector receive more training than individuals in the private sector. The union member dummy is not significant in the second step and is hence just affecting the on-the-job training incidence, just as the two workplace characteristics learning-time and decision-maker. The variable "New knowledge" is significant and positive for both on-the-job training incidence and the conditional number of training days.

Summing up, most of the estimated effects differ between the first and the second step while some are the same. This implies that there are differences between those attributes that determine on-the-job training incidence and those that determine how much training is given conditional that the decision to provide on-the-job training is made.

5 Summary and Conclusions

The purpose of this paper is to examine the determinants of the incidence on-the-job training and the amount of training received. On the basis of the theoretical framework, a set of explanatory variables was chosen and probit, negative binomial and hurdle estimations were undertaken using a Swedish micro data set from 1991 containing about 3,000 observations.

The probit estimation showed that the greater part of the variables, which according to theory were expected to have an influence on the probability of receiving on-the-job training, really seem to affect the incidence of training. For example, occupational group, public sector, firm size and union membership have a positive effect on the probability of receiving on-the-job training while working part-time is shown to have a negative effect. To answer the question of which factors affect the amount of on-the-job training received, a count data model was estimated. Women were shown to receive less training than men, *ceteris paribus,* while public sector, union membership and higher education, to some extent, increase the number of training days. Occupational group does not affect the amount of training as much as it was shown to affect the incidence of training. Taking the examination a bit further, a hurdle model was estimated. This model showed that the factors which affect the incidence and the amount conditional on incidence are not necessarily the same.

The impact of a higher level of education on on-the-job training has been estimated to be positive in most cases, but it should be noted that the highest education level used, academic degree, is never significant in these models. This contradicts the general opinion that it is the highest educated who receive most training. In the models estimated here, where the reference group has elementary school only, completed high school has a positive effect on on-the-job training incidence and the amount of training, both conditional and unconditional on incidence compared to the reference. A lower school certificate increases the unconditional and conditional amount of training compared to the reference, but does not affect the incidence while the education level academic degree stays insignificant as said before.

Another interesting result is that according to the models estimated here, women receive on average a smaller amount of training than men. The reasons for why women receive less training have not been investigated and therefore need further examination, but one reason might be that they generally have more family responsibilities and therefore are more absent from work during certain periods of their working lives. The employer will then be less inclined to invest in training for women than for men.

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