Participation in training and its effect on the decision to retire early

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Abstract
Human capital theory predicts that older workers are less likely to be involved in on-the-job training than younger workers, due to lower net returns of such investments to the worker and the firm. Empirical testing using the European Community Household Panel shows that older workers indeed participate less in training. However, the differential in training incidence between younger and older workers is smaller in countries with an established tradition of lifelong learning (Denmark and Finland). In Europe, training appears to be complementary to formal education, but this is less so the case for older workers. While correcting for self-selection into training, we show that older workers who do participate in on-the-job training are less likely to retire early than workers who are not engaged in training activities. Our findings suggest that investing in training is indeed a valuable policy tool to keep older workers in paid employment.

JEL Classification: J24, J26.

Keywords: Early retirement, on-the-job training, ECHP.

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1 Introduction

This study focuses on on-the-job training of older workers and its effect on the early retirement decision. Our interest stems from the fact that economic theories – human capital theory in particular – suggest that depreciation of human capital plays a role in explaining (early) retirement patterns (Alders, 1999). With ageing of the workforce, the burden on public pensions is expected to increase in the decades to come. From an economic perspective, the relevance of training the older workforce is twofold. Firstly, because acquired skills become outdated as time passes, and as a consequence of skill-biased technological change, training is a way to prevent skills obsolescence (Bishop, 1997). Secondly, training has been shown to improve the employability of workers (Groot & Maassen van den Brink, 2000). These arguments are particularly relevant for older workers, especially in the light of their relatively low participation rate in Europe (OECD, 1999). However, human capital theory predicts that human capital investments (*i.e.* training on-the-job) are lower for older people compared to younger cohorts. The main reason for this is the shorter pay-back period for older workers (Gilbert, 2001). The obsolescence of human capital due to a lack of investments is not only likely to affect life-time income (Ben-Porath, 1975), but also to increase the rate of labour market exit of older workers. It is the aim of this study to investigate training participation of older workers in Europe, and to establish whether or not training can contribute to working longer.

Governments take measures to retain or increase the labour market participation of older workers. However, such policies are almost exclusively focussed on financial incentives, and alternative routes to retirement (*e.g.* Blöndal & Scarpetta, 1999). By its focus on training, the paper contributes to understanding the effects of 'lifelong learning' policies, a concept that is at the core of the policy debate in Europe, especially in light of the ageing workforce. As argued by the European Commission (2003): "Access of workers to training is an essential element of the balance between flexibility and security and the participation of all workers should be supported, taking into account the returns on investment for workers, employers as well as society as a whole", "It is important that there is a significant increase in investment by firms in the training of adults with a view to promoting productivity, competitiveness and active ageing". Although training participation and its effect on wage has received some attention in the European empirical literature (*e.g.* Pischke, 2001), the effect of training investments on retirement has hardly been touched. We contribute to filling this gap.

We first elaborate on country differences in the determinants of participation in on-the-job training. More precisely, we investigate to what extent participation in training is lower for older workers compared to younger age groups. We derive expectations on the determinants of training (*e.g.* education level, work experience) from economic theory, and test to what extent these are different for older workers compared to their younger co-workers in a comparative perspective. Because countries not only differ with respect to the institutional structure of their early retirement schemes but also with respect to their training facilities, we investigate to what extent this could explain differences in training incidence among older workers. In this respect, our study is complementary to a recent study of Arulampalam *et al.* (2004), who investigate participation in training in ten European countries. However, we specifically focus on older workers, while older workers aged over 55 were excluded from their analysis. Additionally, the modelling technique used in our paper, adds to their paper as we specifically correct for possible selection bias due to non-random employment decisions.

Considering the theoretical and empirical discussions on the training incidence of older workers, we conclude that some of the observed characteristics affect both the decision to retire early and/or to participate in on-the-job training. As a result of this endogeneity problem, a model that compares the retirement behaviour of trained older workers (*i.e.* the treated group) with that of untrained older workers (*i.e.* the control group) with equal observable characteristics might lead to biased results. In this study we first test to what extent such an endogeneity problem is observed in the countries under scrutiny. Additionally, we show how the participation in training, corrected for the endogeneity bias, affects the labour market exit behaviour of older workers.

We conclude that compared to younger workers, older workers are indeed less likely to participate in training in Europe. As observed in previous studies, training participation is found to be complementary to formal education – the high educated get more of it. However, this is less so the case among older than among younger workers. Our model estimates show that on-the-job training does contribute to employability of older workers. After correcting for endogeneity of training, we show that the labour market exit rate among older workers who followed training is nine percentage points lower (within a three-year period) than among workers who did not take any training.

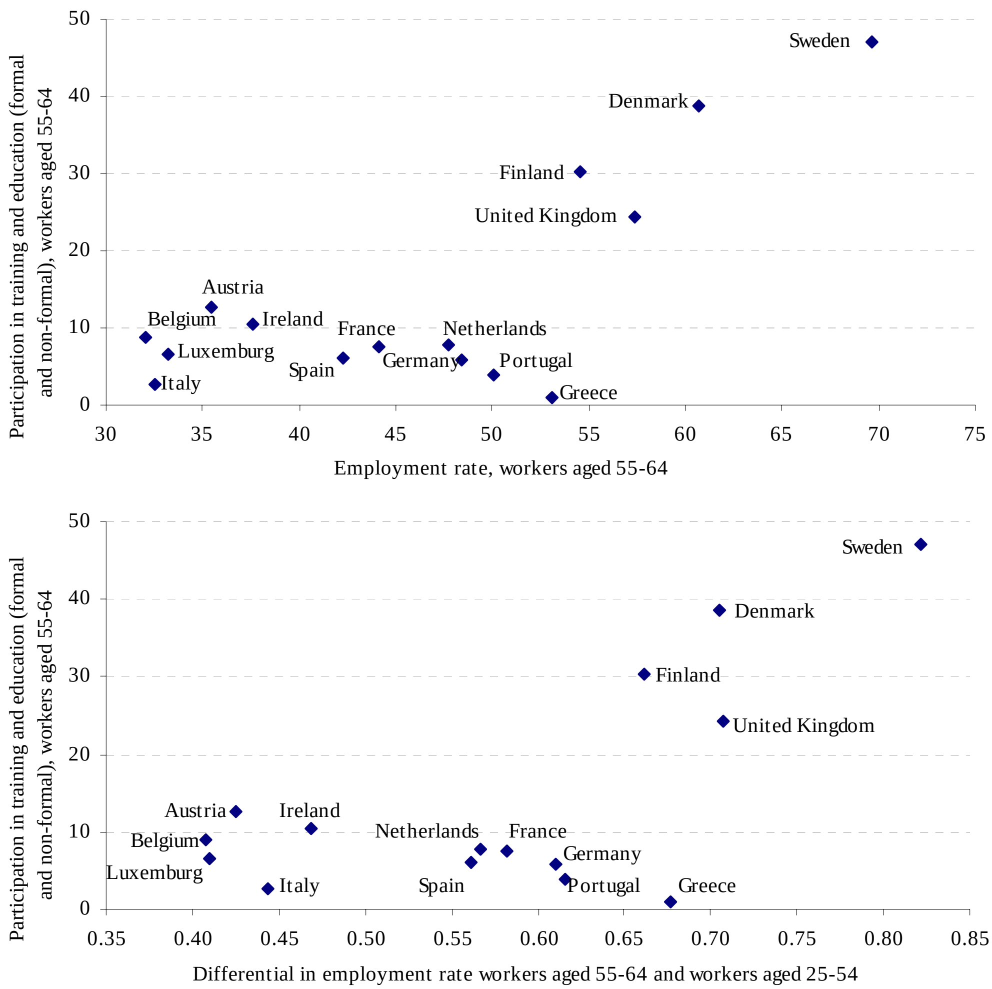
The paper continues as follows. In Section 2 we discuss the economic theories (human capital theory and life cycle theory) that account for the participation in training of older workers, and for the relationship between human capital investments and retirement. In Section 3 we discuss the data used, present some descriptive statistics, and explain the methods used to analyse the participation in training. Section 4 discusses the estimation results of the empirical models for training participation. In Section 5 we estimate the effect of training on the retirement decision. The paper ends with concluding remarks.

2 Theoretical background

2.1 Stylised facts

Stylised evidence in Figure 1 suggests that there is a positive correlation between the labour market participation and training participation of older workers in Europe. This positive relationship holds for males as well as for females. There are, however, large country differences. Of particular interest is the position of the Northern European countries and the UK where above-average training rates are associated with above-average participation rates among older workers. The high training incidence could be explained by the well-established tradition of lifelong learning in those countries (OECD, 2005). In the figure, we also report the training incidence in the age group 55-64, and the differential in employment between the age group 55-64 and the age group 25-54.[1] Again, the association with the training incidence among older workers is positive. Higher levels of training participation among older workers coincide with smaller differences in employment rates between older and prime-aged workers. This, of course, does not say anything about the causal relationship between the variables. But what does theory tell us about the training and employment at older ages?

<u>Figure 1</u>: Participation in training and labour market participation of people aged 55-64 in Europe (top panel), participation in training and labour market participation differential between the age groups 55-64 and 25-54, 2006



Source: Eurostat, 2007.

[1] The lower the differential, the larger the difference in the participation rate between the two age groups.

2.2 Training of older workers

According to human capital theory (Becker, 1964), investments in human capital can be seen as the formation of capital – knowledge- or skill-based – within people. Human capital refers to formal and informal knowledge obtained through pre-school learning, education and job-related training. The latter comprises both formal training (formally organised activities such as apprenticeships, workshops and courses) and informal training (learning by doing or work experience). While Mincer (1962) includes both types of training in his on-the-job training concept, and Arrow (1962) stresses the importance of leaning-by-doing, our focus in this paper is exclusively on formal training. The reason is that information on formal training is readily available in international surveys, whereas information on learning-by-doing is not.[2]

When investing in formal training, both employers and workers must evaluate the costs and benefits of such training. Costs not only include direct costs such as equipment and materials used, but also indirect costs such as the value placed on the time and effort of the trainees as well as on that of their employers. The main expected return on training is an increase in productivity, which is expected to result in an increase in earnings for the worker. However, with respect to the willingness to pay for training, Becker distinguishes between two types of training: general training that also raises the productivity of the worker in other firms, and specific training that only raises the productivity in the firm offering the training. Because returns to general training are not firm-specific, rational employers provide such training only if they can shift the costs to workers. Moreover, workers are usually willing to pay for these costs since the training raises their overall productivity and hence expected overall earnings, regardless of the kind of employer they work for.[3] Specific training, however, mainly yields firm-specific returns and the readiness to pay on the part of the worker is not as clear-cut as with general training. When the employer pays for the specific training and the worker leaves the firm after a while, the employer is faced with a lower productivity because the new worker will not have the same productivity as the trained worker. When the worker pays for the specific training and he is laid off, he will earn a lower wage in his new job because the training he received in his old job is of no value to the new employer (*i.e.* his marginal product is not higher). Both parties thus face a risk of employment disruption. When behaving rationally, they are therefore expected to share the costs of such training (Becker, 1964; Hashimoto, 1981).

Our main interest in this paper being in firm-specific training, these theoretical predictions are important. It is indeed expected that age reduces the probability of participating in such training programmes. This is because net returns to training are

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[2] In our analyses we account for informal learning by including work experience as a variable. Borghans *et al.* (2006) have developed instruments for measuring informal leaning on the job in the Netherlands. They show that workers spend a large amount of time to learning by doing activities, and that informal leaning by doing has an important contribution to the development of knowledge of the workers.

[3] However, see Acemoglu and Pischke (1999) for arguments why employers would pay for general training.

lower for older than for younger workers, for at least four reasons. Firstly, net returns to training are lower because of the shorter payback period for older workers (Becker, 1964). This makes training investments for older workers less effective than for younger workers (Heckman, 2000). In particular, as we explain later in this section, the existence of early retirement opportunities reduces the expected payback period of human capital investments, and discourages both older workers and employers from investing in training.[4] Secondly, because "learning begets learning", training investments at early age are more efficient that training at later age (Becker, 1964; Heckman, 2000). Thirdly, the returns to training are lower at higher ages because of human capital depreciation (Neumann & Weiss, 1995). Hence, at equal educational levels, younger workers are expected to be more likely to follow training than older workers. One of the factors causing human capital depreciation is skill obsolescence (de Grip & van Loo, 2002). As a consequence of technological developments at the workplace, current workers' skills become less valuable in economic terms. Fourthly, it is often presumed that older workers are less trainable than younger workers because their learning ability and their flexibility is considered to be lower (Casey & Bruche, 1981). This is expected to increase the costs and efforts associated with the training activities for older workers.

Theory suggests that, apart from age, a worker's human capital endowments are expected to affect his training probability (*e.g.* Griliches, 1997). Generally speaking, two contradictory perspectives can be distinguished. The accumulation perspective predicts a positive association between a worker's human capital and his participation in training. It is argued that especially people with higher human capital endowments are more likely to accumulate skills and knowledge during their working career compared to people with lower human capital levels. This means that formal education and training are complementary. However, the compensation perspective of lifelong learning holds that it is especially workers with the lowest human capital endowments who need to be trained to make up for their lack of skills and knowledge. Evidence to date supports the accumulation perspective (Arulampalam & Booth, 1998). Concerning the effect of educational level across age groups two competing predictions can be made. On the one hand, because older workers have received their formal education a longer time ago, their knowledge might have become obsolete, suggesting that the effect of former education on the likelihood of participating in training is higher for younger workers. On the other hand, older workers generally have acquired more work experience, thereby raising or updating their human capital. More work experience indicates that the worker has been involved in the informal on-the-job learning process, and most probably in formal learning activities as well. Henceforth, it is not known beforehand whether or not the training propensity across educational levels is different across age groups.

[4] Causality can run both ways here. A lack of training might induce early retirement, yet the mere existence of early retirement might reduce participation in training.

2.3 Training and labour market exit of older workers

The leading theory used to analyse early retirement behaviour of older workers is life cycle theory. The main idea is that a rational worker compares the expected future income stream from the available (early) retirement schemes with that of continued employment and chooses the option that yields the highest utility (see Fields and Mitchell, 1984). Using the life cycle model, Blinder and Weiss (1976) show that the optimal life course of a typical worker consists of four phases: (1) investments in human capital without employment; (2) employment with investments in human capital; (3) employment without investments in human capital; (4) no employment and no investments in human capital, *i.e.* retirement. These phases are associated with back loading earning profiles where workers earn less than their marginal productivity in the first phase, but more in the third phase (Lazear, 1979; Blinder, 1982). This means that there is a wage-productivity gap for workers of older age. A recent study on Canadian data has indeed provided evidence for this wage-productivity gap (Dostie, 2006). To the extent that older workers do take part in training, this could improve their productivity, relative to their wage and hence improve their employability. To put it otherwise, conditional upon taking training older workers are expected to postpone their retirement decision.

2.4 Country differences

Country differences with respect to the effect of age on the training propensity can be expected because of country differences in initial education systems. The literature suggests that the rate of skills obsolescence depends on the type of education the individual has received (Brunello, 2001). In countries with a comprehensive system of education (*e.g.* UK, Ireland), the rate of obsolescence is higher compared to countries where the education system is more stratified and targeted toward vocational skills (*e.g.* Austria, Germany and the Netherlands).

Country differences in early retirement schemes can also account for differences in training incidence and on its effect on retirement. Institutions favouring early retirement (*e.g.* availability of early retirement schemes, benefit generosity) will shorten the payback period of human capital investments. According to the life cycle model, the easier entitlement to early retirement schemes is, or the more flexible these are to use, the higher the early retirement probability. Moreover, the more generous early retirement schemes are, *ceteris paribus*, the higher the utility from retirement and the higher the early retirement probability. Accordingly, highly flexible or highly generous early retirement schemes reduce the probability to participate in training activities at older ages, and also reduce the effectiveness of training as a strategy to postpone retirement. Schils (2005) has come to a characterisation of early retirement routes in Europe that include official pathways such as early retirement schemes as well as less official ones such as unemployment and disability schemes. The characterisation is based on the flexibility of the early retirement routes (how easily can they be accessed?) as well as on their generosity (how high is the replacement rate?). Countries in the liberal tradition (*e.g.* Ireland, UK) have early retirement routes that are not flexible and not generous; Northern European countries have schemes that are flexible but only relatively generous; countries in the Bismarckian tradition (*e.g.* Austria, Belgium, Germany, but also Italy and the Netherlands) have generous schemes, but they are only moderately flexible (Schils, 2005).

3 Data and main variables

For this paper, we use data from the European Community Household Panel (ECHP).[5] We generated a dataset containing panel data (repeated measurement among the same sample of people) for 14 EU countries.[6] For the UK and Germany, the ECHP contains two sources of information: ECHP-specific panel data, and panel data from the national panels.[7] For these countries, we use the latter source. Because of its small sample size, data from Luxembourg are dropped. For all but two countries, data are available for the years 1994–2001. For Austria we have data as from 1995, and for Finland the data start in 1996. The data are organised as a pooled person-year file, with one record for each person at each point of interview. For the analysis, we retained only people of working age, aged 25 to 64. For the analysis of the effect of training on retirement, however, we focus explicitly on people of 50 up to 64 years. Our dataset includes some 70 to 90 thousand respondents aged 25 to 64 per wave across thirteen countries.

The employment status is defined using the self-reported activity status of individuals. People in paid employment, paid apprenticeship or following special training schemes are defined as being employed. Self employed, full time students, and people with small jobs of less than 15 hours per week were removed from the data. A labour market exit is defined as a transition from paid employment to non-employment between two periods of time. Non-employment can mean unemployment, retirement, or another type of economic inactivity, including housework.

A question is included in the ECHP whether the worker is engaged in any job-related training programmes: "*Have you at any time since January (in the previous year) been in vocational education or training, including any part-time or short courses?*".[8] This means that informal on-the-job training is not included, yet we include current job duration to account for this. There is some additional information in the ECHP on the type of training, but the majority of formal on-the-job training is vocational. Only about 14 percent is general training. Information on the duration of the course is not used. On the one hand, evidence suggests that it is more the incidence of a training spell than its duration that is relevant (Pischke, 2001). On the other hand, a reliable measure of the time burden associated to the training is lacking in the data.
A description of the variables used in the analyses can be found in Appendix 1.

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[5] The data are provided by Eurostat and used with their permission. However, the data provider bears no responsibility for the analyses or interpretations presented in this study.
[6] The data included for Sweden are cross-sections.
[7] The British Household Panel Study (BHPS) for the UK and the German Socio-Economic Panel (GSOEP) for Germany.
[8] Note that this question is missing in the Netherlands for 1994.

4 Country differences in the incidence of on-the-job training

Before turning to the empirical model and estimation results, we first discuss evidence on the country differences in participation in on-the-job training in our data. Figure 2 shows the percentages of workers receiving training by age groups and country.[9] In all countries, the percentage of workers receiving training declines with age, as is found in previous studies (OECD, 1999). Riphahn and Trübswetter (2006) hypothesised that if population is ageing, one should observe a behavioural adjustment leading to a relative increase in the training incidence among older workers. This is verified in our data too: while older European workers were 40 percent less likely to receive training at the start of our observation period, the differential has fallen to 30 percent by 2001. Figure 2 further shows some interesting country differences. Scandinavian countries are renowned for having a long tradition of lifelong learning within firms and organisations, and for their policies of promoting 'employability' practice (Antikainen, 2001). One might argue that the second phase distinguished in the life cycle model (phase 2; employment plus training) in these countries is relatively long. This is confirmed here since we find the highest percentages of training across all ages in Denmark and Finland. Although the training incidence is lowest for the oldest age group, still about half of the older workforce participates in on-the-job training. Both countries are characterised by moderately generous early retirement schemes (Schils, 2005), which might be an incentive for older workers to remain employed and to participate in training.

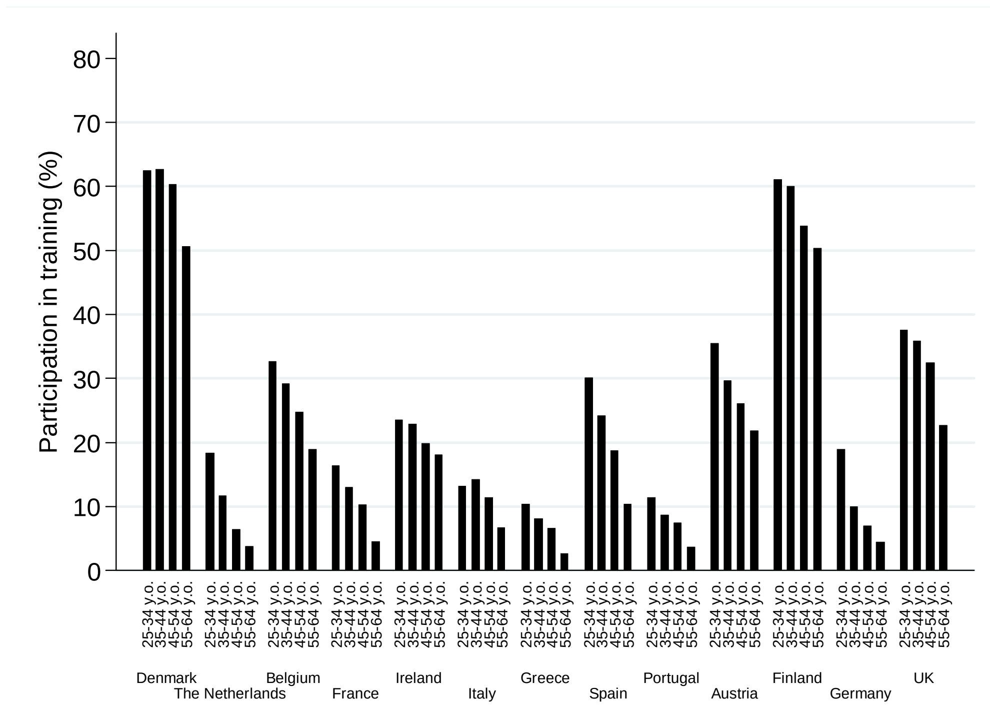
A second group of countries, comprising Austria, Belgium, Ireland and the UK, shows average participation rates in training with about 15 to 20 percent of older workers participating in job-related training programmes. Interestingly, these countries are different when it comes to the generosity of early retirement schemes. Early retirement is most generous in Austria and Belgium, but least generous in Ireland and the UK. The relatively high participation in training of older workers in the first two countries might indicate that these workers are a very select group. People who are still employed at older ages in countries where early retirement is most common and generous are expected to show a higher work attachment, either because of preference or because of financial obligations. Overall, the lowest training participation rates are found in Greece and Portugal. But the participation in training of older workers (aged 55 and over), is also very low in other countries, such as France and the Netherlands, where less than five percent of the workers are participating in formal training. These countries all have moderately or highly generous early retirement schemes (Schils, 2005).

In his study, Pischke (2001) shows that high educated workers are more likely to receive training, but that when low educated do receive training the duration of it is on average longer. Although we have no information on training duration, we do depict the incidence of training by educational level for young and old workers in Figure 3. It shows that the likelihood that one is participating or has participated in on-the-job

[9] These results compare fairly well with other studies on training incidence in Europe (Arulampalam et al., 2004; OECD, 1999).

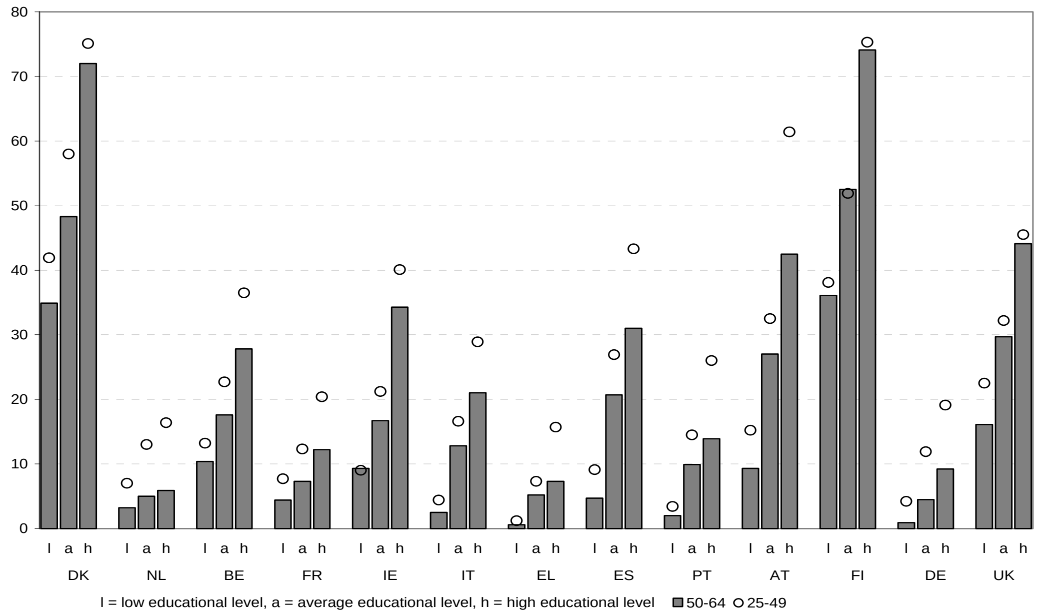
training in the past year increases with the educational level. This supports the accumulation perspective of lifelong learning theories explained earlier. Moreover, this pattern appears to be similar across age groups, albeit at different levels. In three countries, Denmark, Finland and the UK, once we control for education, the differences in training incidence across age groups are small. In the other countries, however, at each educational level, workers aged 50-64 are significantly less likely to participate in training than younger workers. It seems, however, that the difference in training incidence across age group is smaller for the low educated than for the other educational levels. The estimation results will reveal whether the differences from this descriptive perspective are significant.

Figure 2: Training participation in Europe, by age groups, 1994-2001



Source: ECHP 1994-2001 pooled years, own calculations

Figure 3: Training participation in Europe, by educational levels and age groups, 1994-2001



Source: ECHP 1994-2001 pooled years, own calculations

5 Modelling the participation in training

5.1 Model

The dependent variable in our analysis is a binary indicator that takes the value 1 if the individual was involved in formal training in the past calendar year, and 0 otherwise (see Section 3). Because we only observe participation in training for those who are employed sample selection problems are likely to exist, when the employment decision is not random. For example, when workers are a non-random sub-sample of the population due to the fact that these people share higher abilities, estimation results are likely to be biased. To correct for this possible selection bias, we apply a Heckman-type selection model (Heckman, 1976). The standard Heckman model employs a probit model for the selection equation, and an OLS regression for the substantial equation. This is not applicable in our case, since both the dependent variable in the selection equation (employment) and the dependent variable in the substantial equation (training) are binary. We have the following model (van de Ven & van Praag, 1981):

$y_{1i}^{*} = \beta_1 X_{1i} + \varepsilon_{1i}$ (substantive equation)
$y_{1i} = 0$ if $y_{1i}^{*} \leq 0$
$y_{1i} = 1$ if $y_{1i}^{*} > 0$

$y_{2i}^{*} = \beta_2 X_{2i} + \varepsilon_{2i}$ (selection equation)
$y_{2i} = 0$ if $y_{2i}^{*} \leq 0$
$y_{2i} = 1$ if $y_{2i}^{*} > 0$

$$\varepsilon_{1i}, \varepsilon_{2i} \sim N(0,1)$$
$$corr(\varepsilon_{1i}, \varepsilon_{2i}) = \rho$$

We are interested in the estimation of the likelihood of participating in training, y_{1i}^{*} which is a function of X_{1i} representing a matrix of observed variables, and an unobserved error term ε_{1i}, with $i \in 1, ..., N$ representing the individuals. However, y_{1i}^{*} is a latent variable and we only observe a binary indicator y_{1i} that takes the value of 1 if a person is engaged in training and 0 otherwise. In addition, training is only observed for people who are engaged in paid employment, i.e. when $y_{2i}^{*} > 0$. This also is a latent variable, and a function of X_{2i} representing a matrix of observed variables and an unobserved error term ε_{2i}. β_1 and β_2 are vectors of coefficients to be estimated. When the correlation between the error terms of the two equations (ρ) is zero, the non-selection model provides unbiased results. Yet with the correlation term being different from zero, the correction for selection bias is necessary. A joint likelihood function of both equations is then estimated by maximum likelihood. The model was estimated for all respondents (25-64 years old). All the estimations were performed in Stata (StataCorp, 2005).

Covariates included in the probit equation for the participation in training (*i.e.* the substantial equation y_{1i}^{*}) are derived from the theoretical framework exposed above. The main covariates are age (an age dummy for people aged 50 and above), gender, education level, job duration, hours worked, sector of industry and firm size[10], the type of contract, tenure in the current job, a dummy indicating whether or not the current job spell was preceded by unemployment, a variable to account for the level of his job (*e.g.* supervisory task or not)[11], and country and year dummies. Covariates included in the probit equation for employment (*i.e.* the selection equation) are age, gender, education, country and year dummies. Identification of the model is assured by means of exclusion restrictions: the outcome equation includes job characteristics that are absent from the selection model. On top of that, the selection model includes variables that are excluded from the substantive equation and that are expected to account for self selection into employment such as the health status (self reported),

[10] This includes a dummy for workers in the industry, agriculture or construction (the reference includes wholesale and retail, hotel and catering as well as financial and non-financial services. A dummy is included for workers in the public sector. Firm size is only coded for workers in the private sector.
[11] This variable is not included for Germany.

experience of unemployment in the past five years, the labour market of the spouse (when there is one) and the household size. For summary statistics on the covariates, we refer to Appendix 1 (Table A1.1). Since we estimate the model on pooled data we violate the assumption of independent observations when estimating the parameters of the model. This results in a downward bias of the variance of the parameters. This violation problem is solved by using the Huber/White sandwich estimator of variance (Huber, 1967; White, 1980).

5.2 Results

In Table 1 we present the results from the probit model for the likelihood of participating in training. In the first place two models have been estimated on the data. The basic model (Model 1) that includes the variables discussed above, and another model (Model 2) that includes interaction terms for age and education. In addition a model with country specific effects was estimated (but it is not reported here).[12] The Heckman probit model estimated here reports the value of the correlation between the unobserved error terms in the selection and the outcome equation. It is highly significant and negative, suggesting that unobserved characteristics (*i.e.* incorporated into the error term) that increase people's employment probability are negatively correlated to training.

Model 1 does indeed shows that older workers are less likely to participate in training than younger workers (1.5 percent according to the marginal effects). Although significant, this effect is smaller than the above descriptives suggest. This is partly explained by the additional control variables in the model, but especially by the fact that the model explicitly accounts for self-selection in paid employment. A simple probit model that does not correct for selection into paid employment does overestimate the effect of age; the marginal effects fall from 5.5 to 1.5 percent when applying the Heckman model. The model with age-country interactions revealed that the age difference in training participation is significant and larger than average in the Netherlands, France, Greece, Spain, Portugal and Germany. This is in line with the descriptive findings shown in Figure 2.

[12] The results can be obtained from the authors.

Table 1: Model estimates of probit model for the likelihood of participating in training in Europe (with Heckman correction for selection bias), pooled years

	Model 1 Probit		Marginal effects		Model 2 Probit		Marginal effects	
Aged 50-64 (ref: 25-49)	-0.048**	[-3.07]	-0.015**	[-3.18]	-0.051*	[-2.50]	-0.016*	[-2.57]
Aged 50-64, low education					0.087**	[3.64]	0.028**	[3.54]
Aged 50-64, high education					-0.027	[-1.21]	-0.008	[-1.22]
Education (ref: average)								
Low educated	-0.328**	[-23.99]	-0.095**	[-29.65]	-0.339**	[-23.96]	-0.099**	[-28.99]
High educated	0.234**	[22.40]	0.074**	[23.72]	0.235**	[21.58]	0.075**	[22.54]
Female	0.246**	[19.40]	0.076**	[16.70]	0.254**	[20.08]	0.079**	[17.22]
Hour worked per week (log)	0.061**	[4.22]	0.019**	[4.22]	0.061**	[4.23]	0.019**	[4.24]
Temporary contract	-0.037**	[-3.17]	-0.011**	[-3.20]	-0.036**	[-3.11]	-0.011**	[-3.14]
Industry (ref: services)	-0.175**	[-18.76]	-0.052**	[-19.23]	-0.174**	[-18.73]	-0.052**	[-19.22]
Public sector	0.264**	[29.53]	0.083**	[28.72]	0.263**	[29.50]	0.083**	[28.80]
Firm size	0.040**	[23.10]	0.012**	[23.00]	0.039**	[23.07]	0.012**	[23.01]
Job level (ref: non-supervisory)								
Supervisory	0.287**	[24.46]	0.094**	[22.80]	0.287**	[24.59]	0.095**	[22.96]
Intermediate	0.208**	[22.43]	0.066**	[21.41]	0.207**	[22.44]	0.067**	[21.46]
Tenure in years (ref: 15 years or more)								
Less than 1 year	0.279**	[20.89]	0.092**	[19.45]	0.278**	[20.85]	0.092**	[19.49]
1-4 years	0.155**	[14.30]	0.049**	[13.85]	0.154**	[14.17]	0.048**	[13.77]
5-9 years	0.019	[1.67]	0.006	[1.66]	0.017	[1.51]	0.005	[1.50]
10-14 years	0.006	[0.49]	0.002	[0.49]	0.004	[0.28]	0.001	[0.28]
Unemployed before current job	-0.068**	[-6.86]	-0.021**	[-7.05]	-0.066**	[-6.60]	-0.020**	[-6.78]
Country (ref: Denmark)								
The Netherlands	-1.455**	[-64.52]	-0.252**	[-66.63]	-1.446**	[-63.80]	-0.255**	[-67.00]
Belgium	-0.902**	[-39.12]	-0.190**	[-55.61]	-0.896**	[-38.83]	-0.192**	[-55.49]
France	-1.282**	[-60.44]	-0.244**	[-68.23]	-1.274**	[-59.83]	-0.247**	[-68.63]
Ireland	-0.896**	[-37.20]	-0.189**	[-57.46]	-0.888**	[-36.80]	-0.191**	[-57.21]
Italy	-1.121**	[-49.37]	-0.228**	[-71.26]	-1.110**	[-48.62]	-0.230**	[-71.64]
Greece	-1.516**	[-52.51]	-0.243**	[-67.45]	-1.503**	[-51.73]	-0.246**	[-67.93]
Spain	-0.774**	[-36.63]	-0.179**	[-55.67]	-0.765**	[-36.18]	-0.180**	[-55.16]
Portugal	-1.416**	[-60.16]	-0.249**	[-60.88]	-1.409**	[-59.81]	-0.252**	[-61.22]
Austria	-0.628**	[-27.18]	-0.150**	[-37.71]	-0.622**	[-26.94]	-0.151**	[-37.28]
Finland	-0.033	[-1.64]	-0.010	[-1.66]	-0.033	[-1.62]	-0.010	[-1.64]
Germany	-1.335**	[-64.29]	-0.256**	[-70.10]	-1.325**	[-63.43]	-0.259**	[-70.71]
UK	-0.662**	[-33.48]	-0.159**	[-43.65]	-0.658**	[-33.31]	-0.160**	[-43.48]
Year (ref: 2001)								
1994	0.091**	[7.91]	0.028**	[7.65]	0.091**	[7.97]	0.029**	[7.72]
1995	0.179**	[16.70]	0.057**	[15.70]	0.179**	[16.80]	0.058**	[15.81]
1996	0.190**	[18.29]	0.061**	[17.17]	0.189**	[18.36]	0.061**	[17.27]
1997	0.151**	[14.79]	0.048**	[14.04]	0.150**	[14.85]	0.048**	[14.12]
1998	0.107**	[10.71]	0.034**	[10.30]	0.107**	[10.76]	0.034**	[10.36]
1999	0.051**	[5.18]	0.016**	[5.08]	0.052**	[5.23]	0.016**	[5.14]
2000	0.177**	[18.68]	0.057**	[17.71]	0.177**	[18.72]	0.057**	[17.78]
Constant	-0.439**	[-7.61]			-0.435**	[-7.58]		
Chi-square	21988.250				21902.787			
df	35				37			
N	519075				519075			
N-censored	203508				203508			
Rho	-0.375				-0.397			
Chi2-rho	234.135				257.965			

t statistics in brackets
See Appendix for the selection equations
* p<0.05, ** p<0.01

In general, we find support for the accumulation perspective on human capital: having a high education level increases the probability of being engaged in training, whereas having a low education level reduces it. This result is in line with existing studies, who all report complementarity effects between education and training (*e.g.* OECD, 1999; Brunello, 2001; Arulampalam, 2004). The model with interaction between education and age (Model 2), however, shows that this complementarity especially holds for workers younger than 50. For workers in their fifties, having a high educational level as opposed to an average educational level does not affect significantly the probability of receiving training. The difference in training probability at older age, however, is more in favour of the low educated. This suggests that at older age training is used to compensate for low human capital.

The other coefficients included in the model are now briefly discussed. We find that women have a higher probability of being engaged in training than men. This supports the idea put forward by Arulampalam et al. (2004) that women are in higher need of training because they change jobs more frequently or because they have temporarily dropped out of the labour market due to care obligations.[13] The fact that the training incidence is larger among workers with short tenure suggests, on the one hand, that employers – in accordance with theoretical predictions – have a preference for investing in people for whom they can expect a long pay-back period. On the other hand, it could suggest that especially relatively new workers are in need of acquiring additional specific skills.

Studies have shown that workers who experienced periods of unemployment or non-participation have higher human capital depreciation (Mincer & Ofek, 1982). This would suggest that such workers would engage in more training to compensate for this. However, we find that having experienced an unemployment spell before the current job reduces the likelihood of participating in training. A possible explanation for this is that the unemployment experience is likely to lead to unemployment later in life (Gregg, 2001), which in itself is conducive to uncertainty about the net pay-offs of training. It is also observed that the uncertainty associated with temporary contracts is conducive to lower training incidence. This confirms the results by Arulampalam et al. (2004). We find that the higher probability of participating in training for people on temporary contracts is highly correlated with age. For the youngest workers, the effect of a temporary contract on the probability of training is positive, while for older workers reverse effects are found, with lowest probabilities of training among workers on a temporary contract. As mentioned earlier, training older workers in general is more costly and especially not profitable if they are employed on a temporary contract. With the growing prevalence of temporary and flexible contracts in Europe, this reduced involvement in training of people employed on flexible contracts tends to have the effect of reducing the average skill level of the workforce in the future (OECD, 1999).

As far as the sector of activity is concerned, we looked at differences in training between the service sector and the industrial sector and between the public sector and the private sector. Starting with the former, we find higher training probabilities for service-sector workers, regardless of whether these are commercial or non-commercial services. In a study of the OECD (2001), two explanations are given for higher training among service-sector workers. The first is the relatively higher education level of workers in the service sector compared to workers in the industrial

[13] Despite the fact that the ECHP does not contain information on the entire work history, looking at current job durations we find that that these are indeed shorter for older women (aged over 45) compared to men of the same age. For example, about 71 percent of older male workers have been employed for more than ten years in the current job compared to only 61 percent of older female workers. This leads us to suspect that women indeed experience more job changes and discontinuous working careers.

sector. This has, however, already been accounted for in our model. The second explanation is to be found in changes in the information technology. It is argued that workers in the service sector use computers most intensively and with the rapid development in this sector, continuous retraining is necessary to keep the workers up-to-date with the new software programmes. In addition, we find that public-sector workers have a higher probability of participating in training. The most likely explanation for this finding is that training activities are more common in the public sector, being less subject to market competition than employers in the private sector. Firm size (only modelled for workers in the private sector) has a positive effect on the training incidence. This is probably due to the fact that large firms can more easily afford training (both in terms of the direct costs of it as well as in terms of forgone production by workers during the training), and that the internal market of large firms offers more possibilities to worker and employer to profit from the training investments.

Broadly speaking, the country dummies reflect the descriptive statistics in Figures 1 and 2. More interestingly, we have replaced the country dummies by indicators for the flexibility and the generosity of the retirement routes (results are reported in Table A2.1 in Appendix 2). As expected, the generosity of the early retirement route has a negative effect for the workers aged 50 and above. The index for flexibility of the retirement regime shows a positive effect on training participation, and that effect is larger for older workers. Apparently, flexibility of early retirement arrangements and life long learning are positively correlated. To be more specific, in countries where the early retirement schemes are most easy to access or where workers have a larger choice set with respect to the age at which to retire, older workers have a higher possibility of participating in training. One might argue that both the older worker and the employer are willing to invest in the training, since the exit moment is not necessarily close by. It should be noticed that flexibility is highest in the Scandinavian countries, where training participation in general is highest as shown earlier.

The model in Table 1 was also estimated for all countries separately. In a simple probit model, the age dummy was found to be negative and significant in all countries, except the UK. Therefore, the difference in training participation depicted in Figure 2 for the UK is due to differences in observed characteristics of the workers. In the probit model that controls for selection into paid employment (see Appendix 2), a negative age effect is found in almost all countries, but it is not significant in France, Ireland, Italy and Finland. The age dummy is positive but not significant in Austria and the UK. It therefore seems that self-selection in paid employment at later age at least explains part of the difference in training intensity in EU countries.

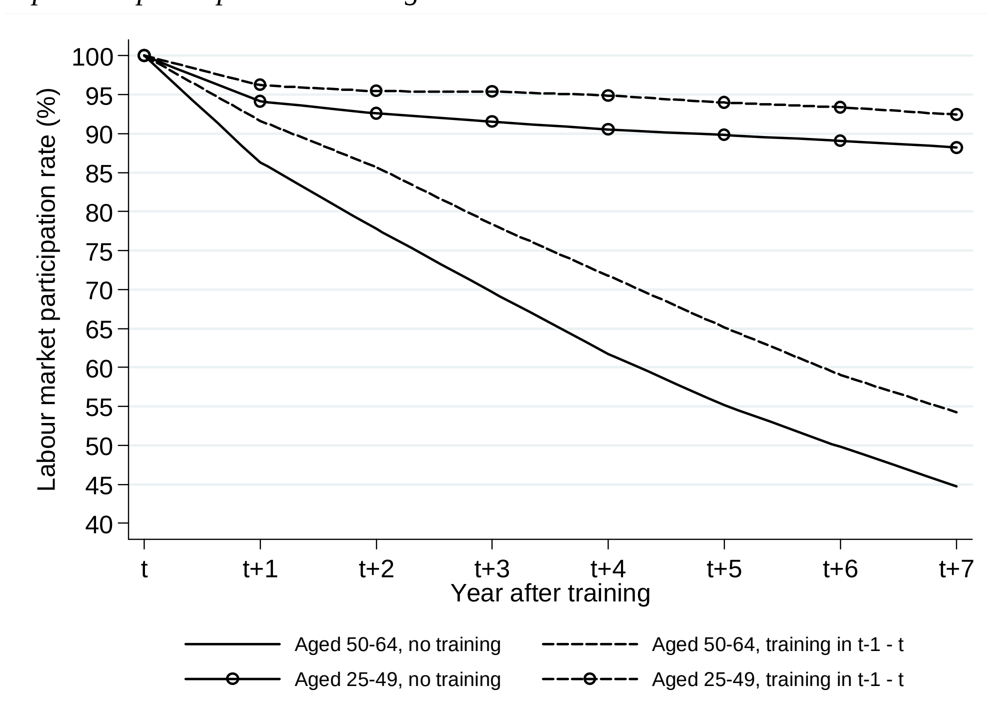
6 Training and labour participation

6.1 Stylised facts

The relationship between human capital and labour mobility at later age has received some attention in the literature. It has been shown that high educated older workers have a lower probability to experience the termination of their contract compared to low educated workers (Peracchi & Welch, 1994), that they have a more stable employment pattern (Blau, 1994), and that the likelihood they retire is lower (Berkovec & Stern, 1991). There is, however, not much research on the effect of training on the labour market mobility at later age. The second main question of this paper is whether or not participation in training reduces the probability of exit from the labour market. That would imply that increased supply of training for older workers might have an effect on their labour participation.

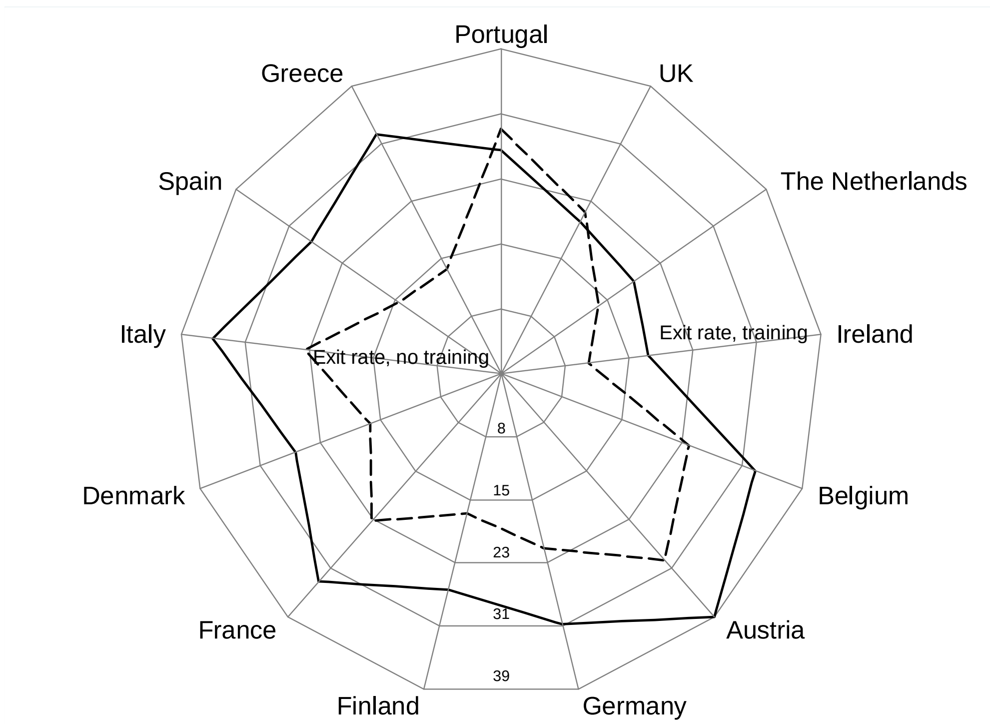
To get a first impression of this, Figure 4 shows the percentages of workers (young, and old) who remain in the labour force after year *t*, respective of whether or not they have received training between *t*-1 and *t*. The rate of labour market exit is then represented by the distance between the line and 100%. Exit now comprises all pathways out of paid employment, *i.e.* a transition to unemployment, inactivity or retirement. For the group aged 50-64, entry into retirement is the primary reason for leaving the labour market. We conclude that on average the percentage of younger workers (25-49) leaving employment is about five percentage points lower when workers participate in training than when they do not participate in training. For older workers (50-64), the difference is twice as large. For example, after three years 78.3% of those we received training recently are still employed while the employment rate of those we did not receive training is 69.6%. To put it otherwise, the exit rate out of paid employment in a three year period is 8 percentage points lower among older workers who received training compared to those who did not.

Figure 4: Labour market participation rate over time, depending on whether or not respondent participated in training between t-1 and t



In Figure 5 we plot the labour market exit probabilities within a three-year period by country, for older workers who have not yet reached the pension age. The country differences in the effect of training for the labour market exit rate of older workers are large.[14] The difference in exit probabilities between older workers with and without training is largest in southern European countries and Denmark. Small differences are found in the Netherlands and the UK. Based on these descriptive statistics, one would conclude that training increases the labour force participation of older workers, in some countries more than in others. However, from the discussion in the previous section, we learned that many of the factors affecting the decision to participate in training of workers, also affect the exit decision (*e.g.* age). Consequently, we expect the training outcome not to be independent of the observed exit outcome, which previously gave us reason to use a selection model for the participation in training. In other words, workers are expected to self-select into training: older workers who expect to continue working are more likely to participate in training than workers who expect to retire early. Consequently, we have reason to believe that participation in training is an endogenous regressor in the early retirement decision. If this is true, the incorporation of a training dummy into the exit equation as in the above model yields biased results that need to be treated adequately.

Figure 5: Labour market exit rate of older workers (50-64) between t and t+3 in relation to participation in training between t-1 and t



[14] In the figure, the countries are sorted according to the difference in exit rate between those who followed training and those who did not.

6.2 Empirical models

In the remainder of the paper we will focus on the effect of training on the probability of leaving the labour market. Rather than focussing exclusively on the immediate effect of training (exit between *t* and *t*+1), we extend to the exit decision between *t* and *t*+3. For the exit model between *t* and *t*+1, we focus on workers aged between 50 and 63. For the transition model between *t* and *t*+3, we only focus on workers aged between 50 and 61. In this way we ensure that respondents have not yet reached the formal retirement age by the end of the observation period.

Heckman selection model
One way of dealing with the issue of endogeneity is to apply a Heckman selection model. Provided there is self-selection into training, the approach consists of estimating the probability of training z_{it}^* in a first step, and use the generalised residuals from this first step probit regression in the outcome regression for exit from paid employment y_{it}^* (Heckman, 1978, 1979). The model is written as follows:

$$y_{it}^* = \beta X_{it} + \gamma z_{it-1,t} + \varepsilon_{it}$$
$$y_{it} = I(y_{it}^* > 0)$$
$$z_{it-1,t}^* = \alpha X_{it} + \delta q_{it} + \kappa IM_{it} + \mu_{it} = \pi W_{it} + \nu_{it}$$
$$z_{it-1,t} = I(z_{it-1,t}^* > 0)$$
$$\begin{pmatrix} \varepsilon_{it} \\ \nu_{it} \end{pmatrix} \sim NID(0;\Sigma)$$

In the outcome equation, y_{it} represents the probability of leaving the labour force between two time points. The choice equation $z_{it-1,t}$ represents the participation in training on-the-job. This equation contains a selection term (*IM*, for the inverted Mills) for the employment status. The model for selection into paid employment is similar to the model applied in Section 5.1, albeit that here the model is estimated in two steps. Identification of the selection model into paid employment is ensured by the inclusion of household level variables, health variables and unemployment history. Identification in the outcome equation is ensured by the inclusion of an instrument (q_{it}) in the choice equation that is absent from the outcome equation. The instrument used indicates whether or not the employer offers training opportunities. It is self-reported by the respondent. The correlation between this variable and actual training participation is 0.37. However, the variable is absent in the UK and only known in one single year in France. These two countries were therefore dropped from the analyses. In Greece, the variable is only available as from 1996.

The strategy is to estimate α, δ and κ with a probit model, to retrieve the generalized residuals from that model ($E(\nu_{it}|W_{it}\, z_{it-1,t})$), and to introduce this so-called control function estimator in the outcome equation (Vella & Verbeek, 1999). The control function is computed as follows:

$$E(\nu_{it} \mid W_{it} z_{it-1,t}) = \lambda(W_{it}\pi) = (1 - z_{it-1,t}) \frac{-\phi(W_{it}\pi)}{\Phi(-W_{it}\pi)} + z_{it} \frac{\phi(-W_{it}\pi)}{1-\Phi(-W_{it}\pi)}$$

where ϕ and Φ represent the normal density function and the cumulative normal density function, respectively. The final model to estimate takes the following form:

$$y_{it} = \beta^* X_{it} + \gamma^* z_{it-1,t} + \upsilon\lambda(W_{it}\pi) + \varepsilon^*_{it} .$$

A simple test for endogeneity consists of testing that the parameter of the control function is different from zero. The model was used to explain exit decisions between *t* and *t*+1 and *t* and *t*+3.

6.3 Results

In Table 3 we present the results from the probit model for the likelihood of exiting out of employment between *t* and *t+3*. We focus the discussion on the former model mainly because of the time-lagged productivity effects of training, *i.e.* it takes time to observe the effects of training participation. Several models have been estimated. The basic model (Model 1), a model (Model 2) that allows for interaction between training and education, a model (Model 3) in which the country dummies are replaced by indicators for the country's early retirement regime, and finally a model (Model 4) that allows for interaction between these indicators and training. Control variables include age, gender, weekly hours worked, type of contract, level of job, sector of industry, tenure, unemployment history country and year. The results from the first step estimation – for selection in paid employment and for self-selection in training – are reported in Appendix 3, Table A3.1. As mentioned, we also estimated a model for the transition out of employment between *t* and *t*+1 and these results are presented in Table A3.2 (Appendix 3).

Model 1 shows that training indeed reduces the exit probability out of paid employment. The marginal effects indicate that the probability of experiencing an exit from paid employment within a three-year period equals 25.1% for an average worker who did not follow training. This probability is reduced by 9.7 percentage points in the case of training. A Chi-squared test for the significance of the self-selection term revels that it is significant at the 5% level. For comparison, the exit probability within a year equals 10% for an average worker without training. The marginal effect of training being 6.3% (Table A3.2). These findings suggest that there are returns to schooling in terms of employability even at later age.

Apart from the known fact that the high educated retire later (Berkovec & Stern, 1991), we do not observe any significant variation in the effect of training on exit from the labour market between older workers with different education levels (Model 2). From this perspective, we can conclude that training is equally effective in increasing employability at all educational levels.

Table 3: Results from Heckman selection model (two-step) for exit from paid employment between t and t+3, model coefficients and marginal effects[1]

	Model 1			Model 2		Model 3		Model 4	
	Coeff		Marg eff	Coeff		Coeff		Coeff	
Train	-0.348**	[-2.90]	-0.097	-0.310*	[-2.42]	-0.195*	[-2.54]	-0.074	[-0.23]
Lambda	0.134*	[1.99]	0.043	0.101	[1.47]	0.049	[1.07]	0.015	[0.32]
Education (ref: average)									
Low educated	0.062	[1.73]	0.020	0.054	[1.47]	0.035	[1.05]	0.041	[1.24]
High educated	-0.210**	[-5.31]	-0.064	-0.203**	[-4.70]	-0.287**	[-7.61]	-0.282**	[-7.47]
Train * low educated				0.115	[1.28]				
Train * high educated				-0.035	[-0.44]				
Age	0.130	[0.97]	0.041	0.125	[0.94]	0.179	[1.35]	0.170	[1.29]
Age^2/100	0.008	[0.06]	0.002	0.012	[0.10]	-0.039	[-0.32]	-0.030	[-0.25]
Female	0.078*	[2.44]	0.025	0.077*	[2.40]	0.069*	[2.19]	0.070*	[2.21]
Country (ref: Denmark)									
The Netherlands	-0.179*	[-2.08]	-0.054	-0.157	[-1.80]				
Belgium	0.268**	[3.21]	0.092	0.285**	[3.38]				
Ireland	-0.311**	[-3.54]	-0.089	-0.293**	[-3.32]				
Italy	0.235**	[3.17]	0.079	0.258**	[3.43]				
Greece	0.216*	[2.24]	0.073	0.240*	[2.46]				
Spain	-0.072	[-0.96]	-0.022	-0.052	[-0.68]				
Portugal	-0.202*	[-2.53]	-0.061	-0.178*	[-2.19]				
Austria	0.544**	[7.46]	0.196	0.559**	[7.59]				
Finland	0.151*	[2.22]	0.050	0.151*	[2.21]				
Germany	0.164*	[2.15]	0.054	0.185*	[2.41]				
Year (ref: 1998)									
1994	0.273**	[7.95]	0.092	0.274**	[7.99]	0.263**	[7.88]	0.261**	[7.83]
1995	0.212**	[6.59]	0.070	0.212**	[6.58]	0.201**	[6.33]	0.196**	[6.17]
1996	0.188**	[6.95]	0.062	0.188**	[6.93]	0.194**	[7.24]	0.192**	[7.14]
1997	0.107**	[5.03]	0.035	0.107**	[5.03]	0.110**	[5.22]	0.109**	[5.15]
Hour worked per week (log)	-0.389**	[-7.38]	-0.124	-0.390**	[-7.40]	-0.368**	[-7.07]	-0.368**	[-7.06]
Temporary contract	0.180**	[3.81]	0.060	0.182**	[3.86]	0.204**	[4.32]	0.204**	[4.33]
Industry (ref: services)	0.072*	[2.22]	0.023	0.074*	[2.27]	0.097**	[3.03]	0.101**	[3.14]
Public sector	-0.074*	[-2.15]	-0.023	-0.078*	[-2.26]	-0.035	[-1.04]	-0.040	[-1.19]
Firm size	0.017**	[2.64]	0.005	0.017*	[2.57]	0.017**	[2.70]	0.016*	[2.47]
Job level (ref: non-supervisory)									
Supervisory	0.050	[1.07]	0.016	0.046	[0.98]	0.060	[1.34]	0.050	[1.10]
Intermediate	0.053	[1.42]	0.017	0.050	[1.35]	0.085*	[2.36]	0.076*	[2.11]
Tenure in years (ref: 15 years or more)									
Less than 1 year	0.162**	[2.58]	0.054	0.165**	[2.62]	0.150*	[2.41]	0.152*	[2.45]
1-4 years	-0.042	[-0.94]	-0.013	-0.041	[-0.91]	-0.072	[-1.64]	-0.067	[-1.52]
5-9 years	-0.301**	[-6.62]	-0.088	-0.299**	[-6.57]	-0.337**	[-7.55]	-0.331**	[-7.42]
10-14 years	-0.238**	[-4.58]	-0.071	-0.237**	[-4.55]	-0.278**	[-5.41]	-0.274**	[-5.33]
Unemployed before current j	0.161**	[3.53]	0.053	0.162**	[3.54]	0.175**	[3.84]	0.171**	[3.76]
Flexibility						0.117**	[3.06]	0.155**	[3.82]
Generosity						0.336**	[7.91]	0.318**	[7.13]
Train * Flexibility								-0.235**	[-2.76]
Train * Generosity								0.148	[1.37]
Constant	-6.781	[-1.85]		-6.683	[-1.82]	-8.967*	[-2.47]	-8.766*	[-2.41]
Chi-square	1648.072			1651.424		1509.245		1513.270	
df	33			35		25.000		27.000	
N	23173			23173		23173		23173	

t statistics in brackets
* p<0.05, ** p<0.01

1: Marginal effects are computed at training=0 and at the mean of the other variables. For dummy variables the marginal effects represent the effect of a change from 0 to 1.

When replacing the country dummies by indicators featuring the country's early retirement regime, we find that – according to our expectations and earlier research (*e.g.* Schils, 2005) – a higher flexibility and a higher generosity of early retirement arrangements increase the exit probability of older workers (Model 3). Training participation only seems to make a difference in more flexible retirement regimes. To be more specific, in countries where early retirement schemes are most easy to access or where the older worker has a larger choice freedom with respect to the age at which to retire, training participation is most effective in reducing early exit. We already observed that training participation as such is higher for older workers in flexible retirement regimes, which might explain the lower exit probabilities in these regimes.

In countries with generous pension systems, training seems to have no significant effect on the retirement decision.

7 Conclusion and policy implications

The standard prediction from human capital theory is that older workers are less likely to be involved in on-the-job training than younger workers. This is because of the expected lower net returns of such investments, both to the worker and to the firm. However, because the (working age) population is ageing in Europe, it is becoming increasingly important to invest in the employability of the older workforce. In the recent past, governments have shown more interest for reforming the pension systems and removing financial incentives to early retirement. But this might just not be enough to keep the older workers in employment, and additional measures aiming at increasing the skills of the older workforce could be are necessary. In this paper, we investigated to what extent older workers in Europe receive on-the-job training, and to what extent such investments contribute to postponing the retirement decision. We have done this using data from the European Community Household Panel.

We have shown that older workers do indeed participate less in training than younger workers. The probability that workers aged 50 to 64 do participate in training is 1.5 percentage points lower than that for younger workers. However, this differential in training incidence is significantly smaller in countries with a well-established tradition of lifelong learning, such as Denmark and Finland. These countries are also characterised as having a more flexible early retirement system, in which there is more freedom of choice as to the age at which to retire, yet with rather modest replacement incomes. It therefore seems that in such systems, the older worker and the employer are more willing to invest in the training because they expect larger returns compared to other systems, especially those in which the replacement income after retirement is high (*e.g.* Germany, Netherlands).

After correction for self-selection into formal training, we have shown that older workers who do participate in on-the-job training are less likely to retire early than workers who are not engaged in training activities. Within a three-year period, the difference in exit probability amounts to almost ten percentage points. Our findings therefore suggest that investing in training is indeed a valuable policy tool to keep older workers in paid employment. This effect is particularly strong in countries with a flexible pension system.

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Appendix 1: Summary of covariates

Table A1 shows the descriptive statistics of the explanatory variables used to estimate the models. Rather than imposing a quadratic form on the relation between age and the dependent variables, we included age categories in the training participation models. With respect to gender, several approaches are found in the literature. It is often argued that the labour market participation decision is different for men and women, which has induced many authors to estimate separate models for men and women. Our main focus in not to test gender difference and therefore we include a gender dummy in both our training and retirement models. However, we have estimated models with gender-interaction terms and report the observed differences when necessary. In the selection equation for employment, we further included self-reported health on a three-point scale, ranging from bad to good health. Several authors, including Lindeboom and Kerkhofs (2004), have noted that using self-reported health measures might lead to exaggerated coefficients because of the endogeneity problem with health and employment, i.e. factors that affect the employment decision might also affect the individual's health status (*e.g.* age). In Table A1 we indeed observe that the health status of people in employment is somewhat better than that of the full population, with that of older workers being worse compared to prime-aged workers. Apart from health, we included household size, the employment status of the partner and a dummy indicating any unemployment spell in the past five years in the selection equation. The majority of respondents have a partner, who is employed in about half of the cases.

Human capital indicators included in the training and retirement equations include the individual's education level and tenure. Education is measured as the highest educational level attained by the individual, on a three-point scale ranging from low (ISCED level 0-2) to high (ISCED level 5-7). The majority of respondents have a lower education. Overall work experience is not included in the ECHP and we only include job tenure at the current job. We use this as a proxy for informal training, or learning-by-doing. It is available in a continuous trend up to ten years or more and we converted it into a dichotomous variable with six classes. Job characteristics included in the training and retirement equations comprise type of labour contract, hours worked a week, sector of employment, level of job, firm size a dummy indicating the unemployment history. Because of a limited number of cases, we have to use a rather crude indicator for sector of activity. On the one hand we distinguish between the service sector and industry and on the other hand between the private and the public sector. With regard to hours worked, we included log hours. Finally, using retrospective information we constructed a dummy indicating whether the individual had been unemployed before his current job.

Table A1.1: Summary statistics on covariates included in the models.

Variable	Full population (selection equation)	Employed population (training equation)	Older population (retirement equation)
Aged 25-29	13.73	16.28	
30-34	14.33	17.04	
35-39	14.17	16.67	
40-44	13.36	15.68	
45-49	12.62	14.15	
50-54	11.43	11.19	48.94
55-59	10.24	6.70	38.05
60-64	10.11	2.29	1301
Female	54.09	42.94	38.09
Education is low	42.57	31.52	42.65
average	34.06	38.21	30.34
high	21.88	28.96	26.05
missing	1.49	1.31	0.96
Health is bad	8.25	3.93	7.64
fair	23.66	20.22	30.30
good	67.50	75.19	61.32
missing	0.60	0.66	0.75
Household size (mean)	3.3	3.3	2.9
Partner: none	23.31	24.01	18.06
employed	51.99	55.67	45.57
unemployed	3.23	3.33	2.52
inactive	21.47	16.99	33.85
Any unemployment in past five years	22.46	20.88	11.80
Hours worked a week (mean)		39.47	39.13
Temporary contract		10.57	7.69
Industry		30.70	31.12
Services		69.30	68.88
Public sector employee		33.38	38.93
Firm size: none		17.27	20.15
1-4 workers		12.47	12.46
5-19 workers		17.22	14.95
20-49 workers		15.07	14.89
50-99 workers		10.66	10.93
100-499 workers		14.65	14.32
500 + workers		12.65	12.30
Job level: non-supervisory		60.69	57.51
intermediate		14.51	14.22
supervisory		10.71	12.87
missing[1]		14.09	15.40
Tenure: < 1 year		9.16	4.46
1-4 years		26.83	13.78
5-9 years		17.81	11.33
10-14 years		11.37	9.02
15 + years		29.64	56.84
missing		5.20	4.57
Unemployed before current job		21.70	13.05

[1]Not available for Germany.

Appendix 2: Participation in on-the-job training

Table A2.1: Model for training participation, including flexibility and security index for early retirement routes

	Model 1		Model 2	
Outcome equation: Training participation				
Aged 50-64 (ref: 25-49)	-0.001	[-0.01]	-0.020	[-0.13]
Flexibility	0.577*	[2.19]	0.539*	[2.02]
Generosity	-0.252	[-1.51]	-0.222	[-1.42]
Flexibility, 50-64			0.226**	[3.26]
Generosity, 50-64			-0.177**	[-3.39]
Education (ref: average)				
Low educated	-0.332**	[-3.37]	-0.348**	[-3.69]
High educated	0.255*	[2.56]	0.262**	[2.58]
Female	0.291**	[6.83]	0.277**	[6.57]
Hour worked per week (log)	0.141*	[2.10]	0.147*	[2.20]
Temporary contract	0.022	[0.40]	0.017	[0.32]
Industry (ref: services)	-0.176**	[-7.10]	-0.177**	[-7.07]
Public sector	0.247**	[8.75]	0.249**	[8.55]
Firm size	0.047**	[4.27]	0.048**	[4.46]
Job level (ref: non-supervisory)				
Supervisory	0.340**	[4.12]	0.342**	[4.13]
Intermediate	0.286**	[4.04]	0.287**	[4.06]
Tenure in years (ref: 15 years or more)				
Less than 1 year	0.308**	[3.29]	0.307**	[3.26]
1-4 years	0.133	[1.73]	0.128	[1.68]
5-9 years	0.010	[0.18]	0.003	[0.06]
10-14 years	0.021	[0.42]	0.014	[0.26]
Unemployed before current job	-0.060	[-0.82]	-0.061	[-0.85]
Year (ref: 2001)				
1994	0.029	[0.32]	0.029	[0.31]
1995	0.140*	[2.21]	0.140*	[2.17]
1996	0.206**	[4.92]	0.207**	[4.95]
1997	0.157**	[4.10]	0.157**	[4.10]
1998	0.111**	[4.06]	0.110**	[4.02]
1999	0.060**	[2.62]	0.059*	[2.55]
2000	0.154	[1.26]	0.154	[1.25]
Constant	-2.054**	[-3.69]	-2.090**	[-3.78]
Selection equation: In paid employment				
Aged 50-64 (ref: 25-49)	-0.842**	[-24.24]	-0.842**	[-24.19]
Education (ref: average)				
Low educated	-0.396**	[-3.02]	-0.396**	[-3.02]
High educated	0.388**	[4.20]	0.389**	[4.20]
Female	-0.926**	[-25.31]	-0.926**	[-25.44]
Year (ref: 2001)				
1994	-0.136	[-1.66]	-0.136	[-1.66]
1995	-0.130**	[-2.74]	-0.130**	[-2.73]
1996	-0.099**	[-3.74]	-0.099**	[-3.74]
1997	-0.079**	[-3.57]	-0.079**	[-3.57]
1998	-0.074**	[-5.00]	-0.074**	[-5.00]
1999	-0.056**	[-4.24]	-0.056**	[-4.24]
2000	-0.032**	[-3.31]	-0.032**	[-3.30]
Flexibility	0.086	[0.22]	0.085	[0.21]
Generosity	0.005	[0.01]	0.006	[0.02]
Household size	-0.081**	[-3.00]	-0.081**	[-2.98]
Partner, if any (ref: employed)				
Unemployed	-0.129**	[-2.61]	-0.129**	[-2.61]
Inactive	-0.220**	[-3.22]	-0.219**	[-3.20]
Health status (ref: fair health)				
Bad/very bad health	-0.519**	[-4.50]	-0.519**	[-4.50]
Good/very good health	0.204*	[2.20]	0.204*	[2.19]
Any unemployment in the past 5 y	-0.375**	[-5.02]	-0.375**	[-5.04]
Constant	1.469	[1.52]	1.467	[1.52]
N	519075		519075	
N-censored	203508		203508	
Rho	-0.382		-0.352	
Chi2-rho	8.565		7.018	

t statistics in brackets
* p<0.05, ** p<0.01

Table A2.2: Country models for training participation

	Denmark	Netherlands	Belgium	France	Ireland	Italy	Greece	Spain	Portugal	Austria	Finland	Germany	UK
Outcome equation: Training participation													
fifty	-0.102*	-0.183**	-0.234**	-0.115	-0.105	-0.082	-0.407**	-0.212**	-0.248**	0.121	-0.029	-0.152**	0.037
educat_1	-0.305**	-0.225**	-0.279**	-0.166**	-0.386**	-0.451**	-0.701**	-0.522**	-0.621**	-0.316**	-0.275**	-0.356**	-0.255**
educat_3	0.367**	0.005	0.332**	0.250**	0.421**	0.241**	0.293**	0.278**	0.247**	0.449**	0.434**	0.158**	0.252**
female	0.134**	0.174**	0.020	0.137**	0.207**	0.317**	0.114	0.295**	0.067	0.336**	0.185**	0.184**	0.181**
lnhours	0.298**	0.067	0.322**	0.164**	-0.076	-0.202**	-0.092	-0.198**	0.001	0.149*	0.090	0.095*	0.233**
tempcontr	-0.200**	0.039	-0.046	0.025	-0.076	-0.031	-0.097	-0.049	0.097*	-0.105*	-0.052	0.183**	-0.198**
industry	-0.209**	-0.122**	-0.142**	-0.048	-0.084*	-0.236**	-0.011	-0.215**	-0.226**	-0.342**	-0.085**	-0.175**	-0.129**
public	0.386**	0.048	0.186**	0.353**	0.347**	0.203**	0.164**	0.219**	0.347**	0.137**	0.269**	0.271**	0.388**
pe008	0.042**	0.034**	0.040**	0.043**	0.026**	0.038**	0.058**	0.040**	0.048**	0.076**	0.071**	0.030**	0.030**
supervi	0.114**	0.032	0.283**	0.190**	0.378**	0.398**	0.558**	0.307**	0.378**	0.577**	0.302**		0.229**
interme	0.056	0.080*	0.138**	0.068*	0.247**	0.331**	0.490**	0.185**	0.267**	0.363**	0.151**		0.229**
tenure_1	0.048	0.399**	0.297**	0.379**	0.344**	0.378**	0.257**	0.250**	0.510**	0.435**	0.129*	0.961**	0.080
tenure_2	0.023	0.424**	0.108*	0.055	0.181**	0.114**	0.081	0.053	0.132**	0.186**	-0.032	0.501**	0.159**
tenure_3	-0.049	0.214**	0.004	-0.028	0.019	0.071	-0.012	-0.006	0.020	0.012	-0.120**	0.170**	0.028
tenure_4	-0.100*	0.159**	0.042	-0.000	-0.003	0.111**	-0.047	-0.037	0.037	-0.015	-0.091*	0.052	-0.012
unbjob	-0.145**	-0.046	-0.033	0.005	-0.048	-0.140**	-0.115*	-0.050	-0.010	-0.083	-0.237**	-0.006	-0.077
year_1	-0.092*		-0.580**	-0.009	-0.260**	0.403**	0.583**	0.143**	0.252**			0.322**	0.132**
year_2	-0.050	0.136**	-0.044	0.359**	-0.035	0.269**	0.477**	0.118**	0.225**	0.192**		0.364**	0.199**
year_3	-0.016	0.200**	-0.037	0.462**	0.051	0.245**	0.377**	0.112**	0.155**	0.137**	0.092**	0.353**	0.189**
year_4	-0.027	0.151**	-0.096*	0.476**	0.027	0.123**	0.289**	0.144**	0.142**	0.122**	-0.022	0.302**	0.204**
year_5	-0.017	-0.029	-0.014	0.099*	0.030	0.220**	0.407**	0.078*	0.083	0.113**	0.064	0.279**	0.126**
year_6	0.028	0.097**	-0.003	0.082*	-0.025	0.216**	0.260**	-0.049	-0.019	0.099**	-0.032	0.005	-0.058
year_7	0.017	0.114**	-0.005	0.057	-0.069	0.108**	0.019	-0.064*	0.007	0.084*	0.057	1.219**	-0.060
_cons	-1.051**	-1.819**	-2.115**	-2.236**	-0.933**	-0.708**	-1.733**	-0.126	-1.646**	-1.581**	-0.597**	-2.279**	-1.761**
Selection equation: In paid employment													
fifty	-0.709**	-1.084**	-1.204**	-0.922**	-0.780**	-0.830**	-0.883**	-0.773**	-0.793**	-1.246**	-0.719**	-0.865**	-0.663**
educat_1	-0.368**	-0.550**	-0.379**	-0.380**	-0.561**	-0.618**	-0.295**	-0.444**	-0.480**	-0.415**	-0.309**	-0.259**	-0.139**
educat_3	0.192**	0.397**	0.492**	0.264**	0.616**	0.252**	0.577**	0.474**	0.448**	0.423**	0.280**	0.386**	0.181**
female	-0.395**	-1.227**	-1.009**	-0.722**	-1.214**	-0.995**	-1.297**	-1.113**	-0.931**	-1.016**	-0.276**	-0.771**	-0.762**
year_1	-0.329**		-0.151**	-0.103**	-0.331**	0.085**	-0.170**	-0.236**	-0.204**			0.040**	-0.170**
year_2	-0.237**	-0.322**	-0.197**	-0.075**	-0.305**	0.037**	-0.196**	-0.241**	-0.112**	-0.007		0.026*	-0.142**
year_3	-0.201**	-0.241**	-0.176**	-0.039**	-0.274**	0.029*	-0.199**	-0.231**	-0.084**	-0.001	-0.208**	0.015	0.002
year_4	-0.169**	-0.199**	-0.155**	-0.029**	-0.184**	0.003	-0.180**	-0.183**	-0.064**	0.016	-0.159**	-0.032**	0.036**
year_5	-0.130**	-0.137**	-0.137**	-0.098**	-0.149**	-0.014	-0.101**	-0.146**	-0.059**	0.019	-0.091**	-0.070**	-0.000
year_6	-0.046**	-0.121**	-0.091**	-0.075**	-0.092**	-0.037**	-0.156**	-0.099**	-0.025**	0.042**	-0.053**	-0.014	-0.044**
year_7	-0.049**	-0.033**	-0.068**	-0.031**	0.030*	0.006	-0.090**	-0.059**	0.002	0.025*	-0.015	0.005	-0.155**
hd001	0.089**	-0.201**	-0.010	-0.043**	-0.077**	-0.089**	-0.043**	-0.079**	-0.047**	-0.064**	0.025**	-0.108**	-0.132**
partun	-0.359**	0.298**	-0.403**	-0.197**	-0.395**	0.020	0.144**	-0.018	0.120**	-0.090	-0.205**	-0.208**	-0.603**
partin	-0.752**	-0.137**	-0.701**	-0.383**	-0.125**	0.060**	-0.041	0.178**	-0.116**	-0.310**	-0.592**	-0.189**	-0.483**
badhea	-0.838**	-0.618**	-0.759**	-0.731**	-0.750**	-0.465**	-0.866**	-0.598**	-0.863**	-0.586**	-0.613**	-0.325**	-0.366**
goodhea	0.642**	0.468**	0.395**	0.096**	0.621**	0.067**	0.387**	0.278**	0.306**	0.380**	0.340**	0.150**	0.231**
up5y	-0.719**	-0.251**	-0.693**	-0.452**	-0.417**	-0.251**	-0.148**	-0.358**	-0.120**	-0.234**	-0.793**	-0.472**	-0.335**
_cons	1.251**	2.100**	1.629**	1.558**	1.406**	1.493**	1.017**	1.424**	1.858**	1.511**	1.291**	1.619**	1.686**
athrho													
_cons	-0.267**	-0.373**	-0.019	-0.309**	-0.074	-0.371*	-0.124	-0.347**	-0.011	-0.533**	-0.311**	-0.558**	-0.209**
Chi-square	676.689	435.320	624.363	836.275	671.343	1125.034	625.639	1745.825	961.206	762.418	767.003	2490.480	1134.304
df	23	22	23	23	23	23	23	23	23	22	21	21	23
N	23107	40243	24722	50879	28104	65982	37712	60306	42896	25363	23605	58414	37742
N-censored	4685	13227	8409	17946	12693	32683	20233	30106	15768	9613	6522	20013	11610
Rho	-0.261	-0.356	-0.019	-0.299	-0.074	-0.355	-0.123	-0.334	-0.011	-0.488	-0.302	-0.507	-0.206
Chi2-rho	14.156	23.933	0.037	13.785	0.593	5.505	0.368	24.626	0.013	24.970	16.674	43.124	7.324

t statistics in brackets
* p<0.05, ** p<0.01

Appendix 3: Training and exit from paid employment

Table A3.1: Results from first step selection models for the models for exit from employment between t and t+3

	Selection model 1		Selection model 2	
	Employment		Training	
Age	0.840**	[11.53]	0.039	[0.26]
Age^2/100	-0.872**	[-13.20]	-0.048	[-0.35]
Education (ref: average)				
Low educated	-0.326**	[-14.46]	-0.382**	[-9.48]
High educated	0.443**	[14.71]	0.264**	[6.95]
Female	-0.974**	[-51.92]	0.294**	[5.61]
Household size	-0.034**	[-5.05]		
Partner, if any (ref: employed)				
Unemployed	-0.078*	[-2.32]		
Inactive	-0.006	[-0.33]		
Health status (ref: fair health)				
Bad/very bad health	-0.462**	[-19.37]		
Good/very good health	0.295**	[18.52]		
Any unemployment in the past 5 years	-0.463**	[-17.63]		
Country (ref: Denmark)				
The Netherlands	-0.588**	[-11.44]	-1.795**	[-25.28]
Belgium	-0.768**	[-13.40]	-0.924**	[-12.67]
Ireland	-0.756**	[-14.12]	-0.710**	[-10.52]
Italy	-0.678**	[-13.77]	-0.912**	[-14.85]
Greece	-0.920**	[-17.84]	-1.377**	[-14.15]
Spain	-0.628**	[-12.62]	-0.755**	[-12.45]
Portugal	-0.164**	[-3.12]	-1.113**	[-16.41]
Austria	-0.747**	[-13.92]	-0.556**	[-8.15]
Finland	-0.160**	[-2.96]	0.000	[0.00]
Germany	-0.181**	[-3.75]	-1.455**	[-22.53]
Year (ref: 1998)				
1994	-0.019	[-1.25]	-0.049	[-1.29]
1995	-0.030*	[-2.24]	0.046	[1.35]
1996	-0.017	[-1.46]	0.013	[0.43]
1997	-0.011	[-1.10]	-0.015	[-0.53]
Employer provides training			0.793**	[26.84]
Hour worked per week (log)			0.085	[1.54]
Temporary contract			-0.056	[-1.02]
Industry (ref: services)			-0.142**	[-4.21]
Public sector			0.140**	[4.40]
Firm size			0.004	[0.66]
Job level (ref: non-supervisory)				
Supervisory			0.214**	[5.44]
Intermediate			0.123**	[3.70]
Tenure in years (ref: 15 years or more)				
Less than 1 year			-0.020	[-0.26]
1-4 years			0.046	[0.92]
5-9 years			-0.092	[-1.95]
10-14 years			-0.018	[-0.37]
Unemployed before current job			0.018	[0.36]
Inverted Mills' ratio			-0.191*	[-2.23]
Constant	-18.625**	[-9.30]	-1.601	[-0.40]
Chi-square	7624.087		4952.329	
df	25		33	
N	74678		29827	

t statistics in brackets
* p<0.05, ** p<0.01

Table A3.2: Results from Heckman selection model (two-step) for exit from paid employment between t and t+1, model coefficients and marginal effects[1]

	Selection 1		Selection 2		Outcome		
	Paid employment		Follows training		Exit between t an t+1		Marg.effects
Age	0.697**	[14.50]	0.044	[0.44]	0.018	[0.23]	0.003
Age^2/100	-0.740**	[-17.19]	-0.048	[-0.52]	0.062	[0.91]	0.011
Education (ref: average)							
Low educated	-0.330**	[-16.44]	-0.352**	[-10.32]	0.043	[1.73]	0.008
High educated	0.440**	[17.02]	0.252**	[8.09]	-0.130**	[-4.65]	-0.022
Female	-0.907**	[-53.62]	0.325**	[7.77]	0.092**	[4.20]	0.016
Household size	-0.033**	[-5.24]					
Partner, if any (ref: employed)							
Unemployed	-0.093**	[-3.05]					
Inactive	-0.039*	[-2.34]					
Health status (ref: fair health)							
Bad/very bad health	-0.472**	[-22.32]					
Good/very good health	0.286**	[20.73]					
Any unemployment in the past 5 years	-0.383**	[-16.38]					
Country (ref: Denmark)							
The Netherlands	-0.566**	[-12.61]	-1.769**	[-30.51]	-0.265**	[-4.16]	-0.040
Belgium	-0.778**	[-15.45]	-0.880**	[-13.97]	0.085	[1.44]	0.016
Ireland	-0.662**	[-13.64]	-0.684**	[-11.65]	-0.304**	[-4.94]	-0.045
Italy	-0.650**	[-14.88]	-0.951**	[-17.77]	0.032	[0.59]	0.006
Greece	-0.918**	[-19.99]	-1.497**	[-16.00]	-0.011	[-0.16]	-0.002
Spain	-0.568**	[-12.78]	-0.806**	[-15.52]	-0.124*	[-2.32]	-0.020
Portugal	-0.078	[-1.66]	-1.231**	[-20.53]	-0.272**	[-4.72]	-0.042
Austria	-0.763**	[-16.17]	-0.586**	[-9.75]	0.254**	[4.85]	0.051
Finland	-0.166**	[-3.50]	-0.009	[-0.20]	0.138**	[2.92]	0.026
Germany	-0.204**	[-4.78]	-1.110**	[-23.67]	0.051	[0.94]	0.009
Year (ref: 2000)							
1994	-0.077**	[-5.00]	-0.273**	[-7.58]	0.279**	[7.45]	0.056
1995	-0.089**	[-6.23]	-0.168**	[-5.06]	0.220**	[6.13]	0.043
1996	-0.080**	[-5.96]	-0.190**	[-6.14]	0.189**	[5.50]	0.036
1997	-0.070**	[-5.61]	-0.219**	[-7.44]	0.193**	[5.72]	0.037
1998	-0.061**	[-5.49]	-0.200**	[-7.11]	0.129**	[3.77]	0.024
1999	-0.047**	[-5.21]	-0.236**	[-8.61]	0.050	[1.40]	0.009
Employer provides training			0.739**	[29.76]			
Hour worked per week (log)			0.062	[1.37]	-0.341**	[-9.00]	-0.060
Temporary contract			-0.043	[-0.94]	0.323**	[9.72]	0.067
Industry (ref: services)			-0.144**	[-5.18]	0.054*	[2.38]	0.010
Public sector			0.148**	[5.71]	-0.057*	[-2.38]	-0.010
Firm size			0.010	[1.80]	0.006	[1.30]	0.001
Job level (ref: non-supervisory)							
Supervisory			0.208**	[6.25]	0.024	[0.70]	0.004
Intermediate			0.133**	[4.69]	0.077**	[2.70]	0.014
Tenure in years (ref: 15 years or more)							
Less than 1 year			0.032	[0.54]	0.452**	[10.02]	0.101
1-4 years			0.019	[0.50]	0.125**	[3.99]	0.023
5-9 years			-0.058	[-1.57]	-0.219**	[-6.51]	-0.034
10-14 years			-0.004	[-0.12]	-0.167**	[-4.59]	-0.027
Unemployed before current job			0.010	[0.25]	0.193**	[6.43]	0.037
Inverted Mills' ratio			-0.263**	[-3.61]			
Train					-0.506**	[-5.28]	-0.063
Lambda					0.211**	[3.93]	0.037
Constant	-14.754**	[-11.03]	-1.554	[-0.58]	-3.081	[-1.44]	
Chi-square	10146.110		6735.064		2243.157		
df	27		35		35		
N	118920		44003		39510		

t statistics in brackets
* p<0.05, ** p<0.01