Training in Europe*

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Abstract

Using the first six waves of the European Community Household Panel (ECHP), a large-scale comparative survey collected annually since 1994, we establish some stylised facts about the extent and determinants of work-related training in European Union (EU) countries. We investigate gender differences within and across EU countries in training participation, using decomposition analysis. We focus on: access to "lifelong learning", fixed-term contracts, part-time versus full-time work, public/private sector affiliation, educational attainment, and the individual's position in the wage distribution prior to training. We find that, overall, women are no less likely than men to undertake training and considerably more likely to train in four countries. The differing effects of characteristics and 'returns' can explain the gaps. There is no significant training-age profile for women and a strong negative profile for men. In several countries there is a negative association between fixed-term contacts and training, particularly for men. In most countries and, for both sexes, training is positively associated with public sector employment, high educational attainment and a high position in the wage distribution.

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Introduction

Initial education ensures that individuals enter the labour market with the appropriate level of human capital for their chosen occupation, while on-the-job skills acquisition potentially continues throughout individuals' working lives. It is well-known that cross-country differences in the stock of human capital and in educational systems are important in explaining differences in growth (see *inter alia* Lucas 1988; Romer 1990). Although cross-country differences in work-related training systems, and the degree to which these support continuing learning, are also likely to be important, there is relatively little comparative work investigating the extent and economic impact of continuing work-related training. This is no doubt owing to the fact that harmonized data to facilitate such comparisons became available only very recently (OECD, 1999).

In this paper we establish some stylised facts about the extent and determinants of work-related training in European Union (EU) countries, and how these differ across men and women. In a companion paper, we estimate the impact of this training for workers at differing quantiles of the wages distribution (Arulampalam, Booth and Bryan, 2003). Throughout we use new training data from the first six waves of the European Community Household Panel (ECHP), a large-scale comparative survey collected annually since 1994 The ECHP is a rich source of information on education and work-related training.

While the studies by the OECD (1999), Brunello (2001) and Leuven and Oosterbeek (1999) provided comparative cross-country analysis of training, our paper differs from theirs in the following respects.[1] First, we use harmonized data for the period 1994-1999 for ten European Union countries and hence provide an up-to-date picture of

[1] The OECD (1999) analyse four surveys: the International Adult Literacy Survey (IALS) 1994-5, the European Labour Force Survey (ELFS) 1997, 1991-96 data from the Indicators of Education Systems, and the 1994 Continuing Vocational Training Survey. Leuven and Oosterbeeck (1999) use IALS data for four countries. While Brunello (2001) uses the ECHP, he analyses only waves 1 and 3 and the focus of his analysis is very different. See also Lynch (1994) for a collection of country-specific studies of training.

training across Europe. Secondly, ours is the first study to exploit the panel nature of the harmonized cross-country data to control for unobserved heterogeneity.[2]

A problem with cross-country studies based on micro-data is the enormous complexity of the analysis. Some studies adopt the simplifying strategy of estimating single equations with country-identifying dummy variables capturing any nation-specific effects (see for example, Brunello, 2001). However, in this paper we estimate separate country-specific equations, as do Leuven and Oosterbeek (1999), a procedure that allows the identification of cross-country differences in the impact of observable individual, demographic and institutional characteristics. We also estimate separate equations for men and women, which to our knowledge has not been done before in comparative analysis of training.

We choose to focus on only a few issues in order to tease out, in an economically meaningful way, gender differences across EU countries in training participation, using decomposition analysis. Our interest is in gender differences with regard to the following issues: access to "lifelong learning"; the relationship between fixed-term contracts and training; part-time versus full-time work; public and private sector training; complementarities between education and training; and the individual's position in the wage distribution prior to training. We find that women are no less likely than men to undertake training and considerably more likely to train in four EU countries. The differing effects of characteristics and 'returns' can explain the gaps. There is no significant training-age profile for women and a strong negative profile for men. In several countries there is a negative association between fixed-term contacts and training, particularly for men. In most

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[2] Our work is complementary with earlier studies such as Leuven and Oosterbeck (1999) and Ryan (2001), who examine a subset of our EU countries.

countries and for both sexes, training is positively associated with public sector employment, high educational attainment and a high position in the wage distribution.

1. The Data and Explanatory Variables

Our data are from the first six waves of the European Community Household Panel (ECHP), a large-scale survey collected annually since 1994 in a standardised format that facilitates cross-country comparisons.[3] The education systems of EU countries are very heterogeneous (Ryan, 2001). Because of this – and because we focus only on cross-country differences in work-related training – we exclude individuals under the age of 25 years, paid apprentices and those on special employment-related training schemes.[4] These restrictions minimize the possibility that our analysis might conflate work-related or 'continuing training' with initial vocational education or training.[5]

For each country, our estimating sub-sample comprises employed men and women who are: (i) between the ages of 25 and 54 years and working at least 15 hours per week; (ii) observed in at least two consecutive waves; (iii) not employed in agriculture; and (iv) with valid observations on all the variables used in the training equations. Where the number of missing values was substantial, we also include a dummy variable for missing value observations in order to preserve the sample sizes. The restriction of working at least 15 hours per week was necessary because of the nature of the ECHP data, where – in the first two waves – we were unable to distinguish individuals regularly working fewer than

3 We only have five waves for Austria and four waves for Finland, as they joined the ECHP after 1994. For Britain we use only the first five waves because the format of the training question altered from 1998 onwards.

4 On average, apprentices and those on special training schemes account for only 1.1% of the sampled age group.

5 Despite the harmonisation of the ECHP, what is reported as training may depend partly on country-specific training systems or what is classed as training versus education. Therefore comparisons of absolute training levels may be misleading. However, cross-country comparisons of continuing training are likely to be more robust for two reasons. First, there is typically much less regulation of continuing training than initial

15 hours from those out-of-the labour force. In addition, some important variables like firm size and tenure are only available for individuals working 15 hours or more. Thus our estimating sub-samples will under-represent low-hours part-timers, though for most countries they represent only a tiny fraction of workers.[6] We include in our analysis the ten European countries listed in Table 1.[7]

The form of the training question is as follows: "Have you at any time since January (in the previous year) been in vocational education or training, including any part-time or short courses?". Since this reference period may overlap with the reference period of the previous wave, and to avoid counting long events more than once, where possible we use the starting dates of the course to identify training, which began since the previous interview.[8] We define *training incidence* to take the value one if the employee received any such training and zero otherwise. The framing of this question suggests that the training responses should be interpreted as more formal courses of instruction, rather than informal on-the-job training. A separate question asks about "general or higher education". Participation in these more general courses is very low (average annual take-up by 25-54 year olds is less than 1%) so we are confident that our results are not affected by interactions with countries' differing formal educational systems.

[Insert Table 1 near here]

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training and education. Second, the incidence of general education after age 25 is very low (typically less than 2%), so there is little danger of confusing training and education.

6 Exceptions are Britain (6.2% of the sub-sample), the Netherlands (8.8%) and Ireland (4.0%). In all other countries the proportion of low-hours part-timers is under 3%.

7 We omit Greece and Portugal from our estimation owing to apparent gaps in the training data and because of the smaller estimating sub-samples with usable information. We also omit Germany because the data sets supplied as part of the ECHP have shortcomings for our analysis: the six wave data set derived from the GSOEP survey excludes many shorter training spells (communication from DIW), whilst in the original three-wave ECHP data set, interview dates are treated as confidential, so it is not possible to construct job tenure or know whether training was before or after the previous interview.

8 The modal interview month is October, corresponding to a reference period of 22 months. The British data do not include training dates. However they are derived from the British Household Panel Survey (BHPS), where the reference period only slightly exceeds one year. Since events are generally very short in Britain,

The incidence of training starts by country is reported in row [1] of Table 1**.** These raw data are weighted using the supplied weights (PG003), which account for non-random sample selection due to the survey design and patterns of individual non-response. The statistics can therefore be taken as representative of each country's population. They show that reported training incidence differs considerably across countries. We can for example identify three high-incidence countries – Britain, Denmark and Finland – where each year over a third of individuals begin training courses. In contrast Austria, Belgium, France and Spain form a group of medium-incidence countries, where the proportion of starts ranges from 10% to 16%. Finally, Ireland, Italy and the Netherlands have incidence below 10%. The ranking of countries compares reasonably well (especially for the high incidence countries) with the cross-country comparisons using different data sources reported in OECD (1999).

For each country, rows [2] and [3] show the incidence for men and women separately. In most countries participation rates for women and men are quite similar and in fact the differences are only statistically significant in four countries: Denmark, Finland, Italy and the Netherlands. In all of these, women are considerably more likely than men to begin a training course. We later decompose the gender differentials within each country to see if they arise because of women's different characteristics (for example, in some countries women are disproportionately found in the public sector as the means in Appendix Table A.1 show), or because their characteristics are 'rewarded' differently. We find that, even in countries where men and women have similar training incidences, there can be different, but opposing, effects of characteristics and 'returns' at work.[9]

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there should be little chance of double counting. For France, we do not use training dates as they are missing for the majority of events.

[9] Appendix Table A.2 presents training participation ratios in Europe, disaggregated across our key variables.

2. The Econometric Model

We now turn to our multivariate analysis of the determinants of training starts across the ten EU countries. The observed dependent variable is binary, taking the value of one if the individual started training since the last interview, and zero otherwise. We specify and estimate a static random-effects (RE) probit model separately for each country and gender. A few comments about the choice of specification are in order.

Since we do not have information on the complete history of training receipts by individuals in the sample, we can only model the additional training they receive every year they are in the sample. In order to model the probability of training receipt in a given year conditional on what happened in the previous year via a dynamic model specification, we would need to: (i) select a sample of individuals who are continuously in the sample, and (ii) address the potential endogeneity, caused by the 'initial' conditions problem, using an appropriate instrument (Heckman 1981a, 1981b). Instead, we specify and estimate a static model in order to avoid restricting the sample by throwing out all the individuals who are not continuously present. However, in recognition of the fact that what we observe is receipt of an additional training event, we include quintile group dummy variables to pick up the individual's position in the wage distribution. This should account for the effect of past training, education and work history on the individual's earnings just prior to the receipt of training.[10] Moreover, to avoid problems of simultaneity, we have chosen to measure all explanatory variables at the wave prior to the wave where the training information was elicited.[11] All covariates are time-varying in the model.

[10] Note time-varying covariates (as we have) in non-linear models are sufficient for identification of the parameters of interest (Hyslop, (1999)).

[11] The only exceptions are individuals who changed jobs between waves, and began training in the new job. Then we use job characteristics from the later wave to ensure they correspond to the new job, but retain their personal characteristics from the earlier wave, including their position in the wave distribution. This procedure resulted in changes to the explanatory variables in only 0.4% of cases.

The model estimated here is the traditional random effects probit model which assumes that the distribution of the random effects conditional on the covariates has a standard normal distribution with zero mean and constant variance. One could relax this assumption by allowing for correlation between the unobserved heterogeneity and included covariates (Chamberlain, 1980). One way to allow for this correlation is to include time means of the covariates as additional regressors. However, since all our variables are binary indicators, there is not enough variation in the time means of the covariates to enable us to account for possible correlation. We have therefore not followed this route.

3. Country-specific Estimates of Training Incidence

Our reduced form estimates for each of the ten countries are reported in Tables 2 and 3 for men and women respectively.[12] Although we estimated all the specifications with and without job tenure, there was little difference between the estimates for our coefficients of interest. We therefore report only the results with tenure excluded. For these EU countries (arranged by column in alphabetical order), the tables report marginal effects for our variables of interest.

[Insert Tables 2 and 3 near here]

Lifelong Learning

First, how much does training incidence vary over the life cycle? Training over the working-life cycle might be viewed as 'lifelong learning', a concept that has been made much of by members of the OECD (see for example, OECD, 1999: 134). In this paper, we

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[12] We also estimated these models by restricting the coefficients to be equal across gender but allowing for the variances of the unobserved heterogeneity to be different. This enables one to test for equality of coefficients across gender using a likelihood ratio test. The null of equal coefficients was rejected for all countries at 5% or less significant levels, except for Ireland [p-value=0.11], The Netherlands [p-value=0.07] and Spain [p-value=0.85].

interpret ‘lifelong learning’ as training starts over the life cycle. Human capital theory predicts that younger workers are more likely to be trained than older workers, since the period over which the training investment can be amortised is longer. On the other hand, with rapid skills obsolescence, that period might be relatively short; hence it may be in agents’ interests to train workers of any age. In that case we might observe ‘lifelong learning’ – where continuing training is observed across all age groups.

Our RE probit estimates reported in Tables 2 and 3, which control for other factors affecting training that might be correlated with age, are quite striking in the following ways. First, younger men are typically more likely to be trained. The marginal effects in Table 2 reveal that, in seven out of the ten countries - Austria, Belgium, Britain, Finland, France, the Netherlands and Spain – the training probability is significantly reduced for men 40 and over, relative to the base group of men aged 25-29 by about 3-7 percentage points. In all seven countries, the negative effect is larger in absolute terms for men over 50 than for men 40-49. For Austria, France, the Netherlands and Spain, men aged 30-39 are also statistically significantly less likely to be trained than the 25-29 year olds. In addition, Irish men aged 40-49 are significantly less likely to be trained, whereas in Denmark there is a significant negative age effect for the over 50s only. In only one country – Italy – are men of all age groups are equally as likely to be trained. Interestingly, compared to Ireland where there is a very small age effect, Spain is the only other country where the negative age differentials are the least for men. For example, men aged 30-39 are only 2 percentage points and men aged 40 or more are only 3 percentage points less likely to have started training relative to men aged 25-30*, ceteris paribus*.

Second, and in contrast to the raw data, there is typically no statistically significant difference in the training probability for older women as compared to the base group of women aged between 25 and 29, *ceteris paribus*. There are only a few exceptions: Austrian women in the 30-39 age group are more likely to be trained, as are Italian women in the 40-49 age group. Only in France are women over 50 less likely to be trained than the base group of women aged between 25 and 29.

In summary, after controlling for industry, occupation, firm-size and the like, for women there is virtually no correlation between the probability of starting formal training and age. This result was found in specifications with and without controls for tenure, and might be construed as some evidence of lifelong learning for women. However, there is a significant negative age effect for men in nine out of our ten EU countries. For these men in these countries there is no evidence of 'lifelong learning'.

These gender differences might arise if women are more likely to do jobs requiring multi-skilling and occupation controls are insufficient to control for this; and/or if - relative to men - women have many jobs as they move in and out of the labour market and get trained at each job (for example, because the training is induction training). But unfortunately we are unable to include labour market experience or the number of previous jobs, because this information is not available in the ECHP. However, we do include quintile group dummy variables to pick up the individual's position in the wage distribution for the wave prior to the training start. This should account for the effect of past job history, training and education on the individual's earnings just prior to the receipt of training. We will discuss these results later in this section.

Fixed-term Contracts (FTC)

Some temporary work (for example, vacation employment) is by its nature seasonal or casual. For other jobs, where the work itself does not dictate temporary employment, the job is temporary due to a characteristic of the *employment contract* under which the worker is hired, namely its fixed-term duration. We distinguish where possible between seasonal/casual temporary jobs (which are not covered by formal contracts), on the one hand, and jobs covered by fixed-term or short-term contracts on the other.

European countries have adopted widely varying policies concerning employment protection. In economies where permanent workers have high levels of employment protection, temporary contracts can provide a mechanism enhancing labour market flexibility, since firms can adjust their workforces by varying the number of temporary workers. In Spain and to a lesser extent France, countries characterised by high levels of employment protection, there has been a dramatic growth in temporary jobs over the last 15 years (Dolado et al, 2002; Blanchard and Landier, 2002). The experience of Britain provides a contrast, since weak employment protection has been associated with a low and stable percentage of the workforce in temporary jobs (Booth, Francesconi and Frank, 2002).[13]

Since a FTC is short, human capital theory would predict that a FTC job would be associated with a lower training incidence than a permanent contract, because there is a shorter period over which the training returns can be realized. On the other hand, there are a number of other arguments suggesting that FTCs might be associated with more training starts. First, to the extent that FTC are probationary (as for example in the Netherlands and Austria), training might be offered by firms as a means of learning about worker ability before offering a permanent contract. Second, US evidence reveals that the majority of U.S. temporary help supply firms offer nominally free, unrestricted computer skills training to their contract workers and Autor (2001) suggests that such general training induces self-selection and screens worker ability. Some of our FTC workers might actually be from

[13] Recently, European Union policy-makers have turned their attention to temporary jobs, and required the extension of employment protection to temporary workers Temporary work is increasingly falling under the aegis of European Union (EU) directives, as indicated in the 1999 EU directive concerning the framework agreement on fixed-term work. For information see the Department of Trade and Industry site (http://www.dti.gov.uk/er/europe/directives.htm).

temporary supply agencies (a possibility that we are unable to investigate with our data) and for this reason there might be a positive correlation between training starts and FTCs. Third, in some countries (for instance, Finland, France, Italy and Spain), legislation specifically permits the use of FTCs for training purposes (see OECD, 1999: pp104-5) and this too might contribute to a positive correlation.[14]

Table 2 for men and Table 3 for women report marginal effects for workers on fixed-term contracts (FTC) and separately for casual workers where data permit, relative to the base of permanent workers.[15] For the countries for which we have information about casual work, there is no statistically significant difference between casual and permanent workers in their training probability, with the exception of Danish men and women. It is estimated that in Denmark, women in casual/seasonal jobs are 25.5 percentage points less likely than women in permanent jobs to receive training, *ceteris paribus.* The estimated effect for Danish men is 11.5.

For men, being on a FTC is associated with a statistically significant lower training probability for five countries – Austria, Britain, Denmark, Finland and Spain. In Finland and Spain, this effect is not only statistically significant at the 5% level or more but the estimated effect is also large at about 10-13 percentage points. There is no statistically significant positive association for men for any country.[16] This finding provides some support for the orthodox human capital predictions of a likely negative correlation between

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[14] To the extent that some of these individuals self-classify themselves as being on training schemes, they will be eliminated from the sample, since we drop paid apprentices and those on special employment-related training schemes. However, see also footnote 3.

[15] Our FTC and casual proportions in Table A.1 are lower than those reported in Booth, Dolado and Frank (2002, p. F183). This might be because fixed and casual workers in the ECHP data are only defined for individuals working more than 15 hours/week.

[16] The proportions of men on FTC (as distinct from casual) in these four countries varies considerably. For example, as Appendix Table A.1 shows, both Britain and Austria are characterized by relatively low proportions of workers on FTCs. Finland has a higher proportion, at 8.5% for men and 12.8% of women, while some 22% of Spanish male and female workers are on FTCs. Finland experienced a recession following the Soviet Union break-up.

short jobs and training starts. As reported in Booth, Dolado and Frank (2002) using aggregate cross-country data, there is a significant positive correlation between the proportion of a workforce that is temporary and the strictness of EPL. The negative effect of FTC on training, revealed in Table 2 for men in five countries, highlights a potential further indirect outcome of the EPL. EPL increases temporary contracts, temporary contract workers are less likely to get training, hence EPL through this mechanism affects a country's human capital acquisition. This mechanism may be at work in Finland, for example, where the negative effect of a FTC is quite strong, at 10.3 percentage points, and where a relatively large proportion of men, 8.5%, are covered by FTCs.

For women (Table 3), in contrast, there is a positive correlation between FTC and the training-start probability for France (significant only at the 10% level), and a negative correlation for Denmark (significant at the 1% level) and for Finland (significant at the 1% level). The significant negative effect that was found for men in Finland is also present for women FTC workers in Finland (although of half its magnitude in absolute value).[17]

Part-time

In eight of our ten EU countries, part-time and full-time workers are as likely to start training in any year. Owing to data limitations, our sample includes only part-time workers working at least 15 hours per week, but nonetheless this is a striking result that does not accord with the predictions of human capital theory (which suggests that part-timers get less training as in part-time jobs there are fewer hours in which to capture the returns). The exceptions are Britain and Finland, where part-time men and women are less likely to be trained. The absolute value of the marginal effect is particularly large for British and

[17] The lack of statistical significance of many of the FTC coefficients does not appear to be because FTCs are collinear with the youngest age or bottom quintile group dummies. For example, on average some 30% of

Finnish men. In these two countries, the probability of training receipts for part-time men is estimated to be about 27 percentage points less likely compared to full-time men, *ceteris paribus*. Note, however, that male part-time incidence is very low in both countries (see Appendix Table A.1). While for Dutch women there is a small negative effect, this is statistically significant only at the 10 percent level.

Public/Private Sector

The results in Tables 2 and 3 show that public sector men and women in Belgium, Britain, Finland, France, and Spain are significantly more likely to be trained than their private sector counterparts.[18] Public sector men in Denmark and Ireland, and public sector women in Italy and the Netherlands - are also significantly more likely to be trained. The marginal effect is quite large (about 13 percentage points) in the case of Finnish public sector men and women, and Danish men. Only in Austria does working in the public sector seem to have no effect on training starts for both men and women. For men, only in Italy and the Netherlands is there no statistically significant correlation between training starts and sector.

These overall findings are as expected *a priori*. As noted in Booth (1991: 285), to the extent that private sector firms are more constrained than public sector by the need to make profits, they may be less willing to finance training though fears that trained workers might be poached by rival non-training firms. They might also be subject to greater demand

FTC workers are older than 40, and typically only 30-40% of FTC workers are in the lowest fifth of the wage distribution (an exception is the Netherlands, where the figure is 62%).

[18] Public sector – any size. Notice that Finland and Denmark both have high proportions of women in the public sector affiliation (Finland has 31% (men) and 54% (women), compared to 30% and 59% in Denmark). Other countries with a lot of public sector workers, but not the same gender division, are Belgium, France and Italy. However, in all countries women are more likely to work in the public than the private sector.

fluctuations, making workers redundancies likely and expensive, since the training investment would be lost.

Complementarities between Education and Formal Training

Existing evidence suggests that there are strong complementarities between education and training (see evidence by Booth (1991), Arulampalam and Booth (1998), Brunello (2001) and others). Education levels of the working population – and their dispersion - differ considerably across EU countries, as inspection of the means in Appendix Table A.1 makes clear. Education is categorised according to the International Standard Classification of Education (ISCED), where Levels 0-2 cover less than upper secondary education, level 3 is upper secondary education (e.g. GCE A-levels, baccalauréat) and levels 5-7 cover tertiary education, both university and non-university.

The pattern of our estimates differs from that of Brunello. This is not surprising, as he included non-workers and young people in his analysis, for whom the interaction of educational systems and initial training is likely to be important.[19] He also used ECHP as a cross-section in which countries were pooled. We show that, estimating separate models for each country, *ceteris paribus*, for both men and women, there are seven out of ten countries in which highly educated individuals are significantly more likely to get training than the base group of less than upper secondary level. For both sexes, the common set of countries comprises Britain, Denmark, Finland, Italy and Spain. However highly educated women in France and the Netherlands, and men in Austria and Ireland, are more likely to experience training starts than the base. Only in Belgium does education have no significant effect, ceteris paribus.

[19] He attempted to account for school design in one of his specifications.

In our companion paper (Arulampalam et al, 2003), we suggest that the complementarity of the education and training systems may explain some part of the observed differences in wage inequality across EU countries documented in, for example, Blau and Kahn (1996).[20] [21]

Quintile groups

We are unable to include labour market experience or the number of previous jobs, because this information is not available in the ECHP. However, we do include quintile group dummy variables to pick up the individual's position in the wage distribution for the wave prior to the training start. This should account for the effect of past job history, training and education on the individual's earnings just prior to the receipt of training.

The results in Tables 2 and 3 show that in four countries – Austria, Britain, Finland and France – the lowest paid fifth of workers were less likely to begin training in any year than the highest paid fifth for both men and women. The magnitude of the effects in Finland is particularly large: 23 percentage points for men and 14 percentage points for women. In Ireland, Belgium and Spain, low paid men, though not women, are less likely to train; whilst in Denmark there is only a negative effect for low paid women. In the Netherlands, there is some evidence that women in the bottom fifth of the distribution do get more training, but there is no effect for men. In Italy there does not seem to be any

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[20] Groot and Maassen van den Brink (2000) also argue that training can exacerbate wage inequality.

[21] According to the International Adult Literacy Survey (IALS), Britain has a greater proportion of individuals in the lowest categories for literacy and numeracy than other continental European countries. Moreover, in all continental European countries, a smaller proportion of the younger-age groups are in the lowest categories for literacy and numeracy than the older age groups (suggesting basic skill levels are improving across time in those countries). However this is not the case in Britain, where if anything the older age groups perform better on the skills tests than younger age groups – see Layard et al (2002). Layard, McIntosh and Vignoles (2002) also show that wages towards the top of the wages distribution are similar across most European Union countries. However, at the lower end of the wage distribution, there is considerable cross-country heterogeneity.

effect for low paid men or women. The results also show some negative effects higher up the wage distribution; typically, though, they are smaller.

Unobserved heterogeneity

Tables 2 and 3 report the estimates of rho, the proportion of the total error variance accounted for by unobservable individual heterogeneity (such as unobservable ability or determination). Our preferred model, for both men and women, is the random effects probit, as compared with a pooled cross-sectional model, since the null hypothesis that rho = 0 is easily rejected for all countries. The estimates of rho range from 0.14 for Dutch women to 0.45 for French women, and from 0.22 for Spanish men to 0.43 for French men. They are generally lower in Denmark, Italy, the Netherlands and Spain. In these countries the regressors included in the model have done a relatively good job in capturing individual specific factors, which affect training. But there clearly remain important aspects of individual heterogeneity (perhaps owing in part to the particular institutional framework of each country) that remain unexplained.

5. Gender Differences in Training Incidence

We now investigate how much of the observed gender differences arise because of differing characteristics of women (for example, in some countries women are disproportionately found in the public sector), or because their characteristics are 'rewarded' differently. The latter might occur if the probability of being trained for men differs from that of women because, for example, differences in preferences for training might make one gender more likely to accept training than the other. Alternatively, the probability of being trained for otherwise identical men and women might differ because one gender is more likely to be offered training opportunities by their employers, either because they are less likely to quit or because there is discrimination.

Another reason often put forward in the decomposition literature as to why "returns" might differ is that institutions - as well as preferences and opportunities - might differ across two groups. However, in our case when considering intra-country gender differences, it is hard to think of institutional factors that could lead to differences in returns (where returns to characteristics are given by differences in the marginal effects of particular characteristics), apart from differences in any application of anti-discrimination legislation or in the ease with workers are laid off.

It is common in the literature to use either cross-sectional model estimates or pooled panel data model estimates to look at this type of decomposition of differences between two groups of individuals. Since our model is a random effects model that accounts for unobserved individual specific error components, we take a different route. After the estimation of the RE model, we use the Bayesian framework to estimate for each individual of each gender the unobserved individual-specific component.[22] We then use this in our model, along with the vector of observable characteristics and the estimated coefficients, to predict the probability that the individual will start receiving training during the period. These predicted probabilities are then averaged over the full sample of observations for each gender. The resulting average is the probability of a randomly chosen individual

[22] Estimations were carried out using Stata7 (2001) and Limdep version 8 (2002). The gllamm command in Stata provides the estimate of α_i. These estimates are sometimes referred to as the empirical Bayes predictions or shrinkage estimates (Goldstein, 2003).

undertaking training (Golmuka and Stern, 1990).[23]

For example, take the male sample. For each male in the sample, we not only calculate the predicted probabilities using their characteristics and the estimated coefficients (the impact of the characteristics on the probability), but also use the estimated coefficients from the female model to arrive at the average predicted probability for males if the impact of their characteristics were the same as the females'. In Table 4, the 'own' predicted probabilities are reported along the leading/principal diagonal for each country and the 'other gender' predicted probabilities are reported along the off-diagonal for each country.[24] Thus for men in Austria the average predicted probability of training is 0.142, while for women it is 0.135. But if the males had the same returns as the females, then their predicted probability is 0.121 and if the females had the same returns as the males, their predicted probability is 0.151. The standard errors are then calculated along the lines suggested by Gomulka and Stern (1990).

For each set of four predictions, if the rows are more similar than the columns, then we can say that characteristics are more important than returns in explaining differences, and vice versa. In Italy and Spain the rows are clearly more similar than the columns. So it appears that in these two countries it is basically women's characteristics, which explain their higher training incidence relative to men (though a Spanish man does have a higher training probability than a woman with the same characteristics). As we noted previously, the gender differences in training incidence are statistically significant in Italy and Spain.

[23] Another popular method of calculation of decomposition is to calculate the predicted probabilities using the sample averages of the variables used in the analysis and ignore the individual specific unobservable component. This method, which is appropriate for linear models, is routinely used in decomposition analysis. Since the representative individual given by the sample characteristics is not a real individual we do not use this technique to carry out the decomposition analysis presented here. Although what we have provided here is the most appropriate analysis, the biggest disadvantage of the calculation is that we are unable to provide an inter-country decomposition because of the presence of regional dummy variables in the country specific models (Leuven and Oosterbeek, 1999).

The other two countries with significantly different incidences are Denmark and Finland. In Denmark, holding coefficients constant, female characteristics favour training. But for a woman with typical characteristics, training would be higher with a man's returns. So the two effects oppose one another, but it seems that the characteristics 'win'. In Finland, on the other hand, both characteristics and returns favour female training. This is also the case in the Netherlands, though as the columns are more similar, the effect of returns is the more important. However, as noted, there is no overall statistically significant difference in the training incidence of men and women in the Netherlands.

In the remaining countries the differences in incidence are not significant, but these similarities can mask some competing effects. For example in Austria, female characteristics favour training but they are counteracted by lower returns for women. In Belgium and Britain the picture is more ambiguous. Women with typical characteristics would get less training with men's returns, or with men's characteristics, but on the other hand, men would get less training if they had women's characteristics. In France and Ireland, Table 4 does not suggest any significant differences between the effects of characteristics and returns.

5. Conclusions

In this paper we established some stylised facts about the extent and determinants of work-related training in European Union (EU) countries, and showed how these differ across men and women. Our data source is the first six waves of the European Community Household Panel (ECHP), a large-scale comparative survey collected annually since 1994. We investigated gender differences within and across EU countries in training

[24] If the model had been a random-effects logit one, then the own predicted probabilities would have been the same as the actual raw data training incidence. In probit models such as ours, they are approximately the same.

participation, using decomposition analysis. Our interest was in gender differences with regard to the following issues: access to "lifelong learning"; the relationship between fixed-term contracts and training; part-time versus full-time work; public and private sector training; complementarities between education and training; and the individual's position in the wage distribution prior to training; and.

Our analysis yielded the following stylised facts about training in Europe for employed men and women aged between 25 and 54 years:

- Women are no less likely than men to start on a training course *ceteris paribus*, and in Denmark, Finland, Italy and Spain they are considerably more likely to undertake training (by between 10% and 60%).
- In Italy and Spain, women's different characteristics explain their different training probabilities relative to men. In Denmark and Finland differing returns also seem important. In other countries, similar overall incidences across the sexes can hide the opposing effects of characteristics and returns.
- The countries with the highest - predicted and actual - formal training probabilities are Denmark, Britain and Finland, all with probabilities for both men and women of over 35%. The next highest country was Austria, with just under 15%.
- For women, there is virtually no correlation between the probability of starting formal training and age. This result was found in specifications with and without controls for tenure, and might be construed as some evidence of lifelong learning for women. However, there is a significant negative age effect for men in nine out of our ten EU countries, for whom there is no evidence of 'lifelong learning'.
- For men, being on a FTC is associated with a significantly lower training probability for five countries – Austria, Britain, Denmark, Finland and Spain. There is no statistically significant positive association for men for any country. This

finding provides some support for the orthodox human capital predictions of the likely correlation – negative - between short jobs and training starts. For women in most countries, there is no statistically significant correlation. For the countries for which we have information about casual work, only for Danish men and women is there a statistically significant negative effect of casual work on training.

- In eight of our ten EU countries, part-time and full-time workers are as likely to start training in any year. Owing to data limitations, our sample includes only part-time workers working at least 15 hours per week, but nonetheless this is a striking result that does not accord with the predictions of human capital theory. The exceptions were Britain and Finland, where part-time men and women are less likely to be trained.
- For most of our EU countries, for both men and women, participation in training is higher in the public sector than in the private sector. These findings are as expected a priori. To the extent that private sector firms are more constrained than public sector by the need to make profits, they may be less willing to finance training though fears that trained workers might be poached by rival non-training firms. They might also be subject to greater demand fluctuations, making workers redundancies likely and expensive, since the training investment would be lost.
- For the vast majority of countries, highly educated individuals are significantly more likely to get training than the base group of less than upper secondary level, even taking account of their position in the wage distribution in the previous wave.
- In all countries except Italy and the Netherlands there is evidence that workers in the bottom part of the wage distribution get less training, controlling for other determinants like age and education. But in the Netherlands there is some evidence that the lowest paid are more likely to undertake training.

References

Arulampalam, Wiji and Alison L Booth (1998), "Training and Labour Market Flexibility: Is there a Trade-off?" *The British Journal of Industrial Relations*, December 1998, 36(4) pp521-536.

Arulampalam, Wiji, Alison L Booth and Mark L Bryan, (2003), “Asymmetries in the Training Effect on European Union Wages”, mimeo, University of Essex.

Autor, David H. (2001) “Why Do Temporary Help Firms Provide Free General Skills Training?”, March 2001, MIT Dept. of Economics Working Paper No. 01-03.

Blanchard, Olivier, and Augustin Landier, (2002)”The Perverse Effects of Partial Labour Market Reform: Fixed term Contracts in France,” *The Economic Journal,* 112, F214-244, June.

Blau, Francine and Lawrence Kahn (1996), “Wage Structure and Gender Earnings Differentials: An International Comparison”, *Economica*, New Series, Vol. 63, No. 250, Supplement: Economic Policy and Income Distribution, pp. S29-S62.

Booth, Alison L. (1991), “Job-related Formal Training: Who Receives it and What is it Worth?”, *Oxford Bulletin of Economics and Statistics* 53(3) pp 281-94, August.

Booth, Alison L., Juan Dolado and Jeff Frank. 2002. 'Introduction to the Symposium on Temporary Work.' *The Economic Journal,* 112, F181-F188, June.

Booth, Alison L., Marco Francesconi and Jeff Frank. 2002. 'Temporary Jobs: Stepping Stones or Dead Ends?' June, *The Economic Journal,* 112, F189-F213, June.

Brunello, Giorgio. 2001. “On the Complementarity between Education and Training in Europe.” IZA Discussion Paper No. 309, June. http://www.iza.org/

Chamberlain, Gary. 1980. 'Analysis of covariance with qualitative data', *Review of Economic Studies*, 47, 225-238.

Dolado Juan.J., Carlos Garcia Serrano and Juan F. Jimeno, (2002) “Drawing Lessons from the Boom in Temporary Jobs in Spain,” *The Economic Journal,* 112, F270-F295, June.

Gallie, D. and S. Paugam (2000) *Welfare Regimes and the Experience of Unemployment in Britain,* Oxford University Press.

Gllamm (2001) – Software for the estimation of Generalised Linear Latent and Mixed Models, a routine in Stata by Sophia Rabe-Hesketh, Andrew Pickles and Anders Skrondal.

Goldstein, Harvey (2003). *Multilevel Statistical Models*, 3rd Edition, Kendall’s Library of Statistics 3, Arnold, London.

Gomulka, Joanna and Nicholas Stern (1990) "The Employment of Married Women in the United Kingdom 1970-83." *Economica,* 57, pp.171-199.

Groot, W and H. Maassen Van den Brink (2000) 'State Dependency in Firm-related Training: A Random effects Ordered Probit Model'. Mimeo, Scholar Programme, University of Amsterdam.

Heckman, J. J. (1981a) "Heterogeneity and state dependence", in *Studies in Labor Markets*, ed. S. Rosen, Chicago, Chicago Press.

Heckman, J. J. (1981b) "The incidental parameters problem and the problem of initial conditions in estimating a discrete time-discrete data stochastic process", in *Structural Analysis of Discrete Data with Econometric Applications*, eds. C. F. Manski and D. McFadden, 114-178, Cambridge: MIT Press.

Holmlund Bertil and Donald Storrie (2002) "Temporary Work in Turbulent Times: The Swedish Experience," *The Economic Journal,* 112, F2245-F269, June.

Hyslop, Dean R. (1999), State dependence, serial correlation and heterogeneity in intertemporal labour force participation of married women, *Econometrica*, 67(6), 1255-94.

Leuven, Edwin, and Hessel Oosterbeek. 1999. "Demand and Supply of Work-related Training: Evidence from Four Countries." *Research in Labor Economics,* Vol. 18, pp. 303-30.

Limdep 2002. *Limdep Software, Version 8*, Econometric Software, Inc.

Lucas, Robert E. Jr. 1988. "On the Mechanics of Economic Development." *Journal of Monetary Economics*, Vol. 22, pp. 3-42.

Lynch, Lisa M. 1994. ed. *Training and the Private Sector: International Comparisons.* Chicago: University of Chicago Press.

OECD. 1999. "Training of Adult Workers in OECD Countries: Measurement and Analysis." Chapter 3 in OECD *Employment Outlook*, pp. 134-175, Paris: OECD.

Romer, Paul M. 1990. "Endogenous Technological Change." *Journal of Political Economy*, Vol. 98, No. 5 (part 2), pp. S71-S102.

Ryan, P., (2001) 'The School-to-Work Transition: A Cross-National Perspective', *Journal of Economic Literature*, Vol. XXXIX, March, pp 34-92.

Stata 7 (2000). *Stata Statistical Software,* Stata Corporation, USA.

Table 1: Training Participation across Europe for Men and Women in Employment Aged 25-54 Years

	Austria	Belgium	Britain	Denmark	Finland	France	Ireland	Italy	Netherlands	Spain
Incidence of training starts										
(1) All	0.16 (4)	0.14(6)	0.41 (2)	0.42 (1)	0.34 (3)	0.15 (5)	0.09 (8)	0.06 (10)	0.07 (9)	0.10 (7)
(2) Men	0.16 (4)	0.14 (6)	0.41 (2)	0.42 (1)	0.34 (3)	0.15 (5)	0.09 (8)	0.06 (10)	0.07 (9)	0.10 (7)
(3) Women	0.16 (4)	0.13 (5)	0.43 (2)	0.47 (1)	0.41 (3)	0.16 (4)	0.10 (7)	0.09 (8)	0.08 (9)	0.12 (6)

Notes: Cross-country ranks are in parentheses. Estimates are weighted.

Table 2: RE Training Probits for Selected Variables (tenure omitted) - Marginal Effects (standard error) for Men

Variable	Austria	Belgium	Britain	Denmark	Finland	France	Ireland	Italy	Netherlands	Spain
30-39 year old	-0.031*	0.001	-0.017	-0.012	-0.039	-0.025**	-0.014	-0.001	-0.025***	-0.020**
	(0.018)	(0.020)	(0.022)	(0.027)	(0.033)	(0.011)	(0.014)	(0.007)	(0.009)	(0.010)
40-49 year old	-0.053**	-0.045**	-0.074***	-0.037	-0.067*	-0.066***	-0.033**	-0.010	-0.056***	-0.027**
	(0.021)	(0.022)	(0.025)	(0.028)	(0.035)	(0.012)	(0.016)	(0.007)	(0.010)	(0.011)
50-54 year old	-0.097***	-0.074***	-0.078**	-0.091***	-0.105**	-0.107***	-0.025	-0.013	-0.074***	-0.032**
	(0.030)	(0.027)	(0.033)	(0.035)	(0.042)	(0.017)	(0.019)	(0.009)	(0.014)	(0.014)
Fixed term contract	-0.069*	0.036	-0.098*	-0.125**	-0.103***	0.005	0.001	-0.002	0.009	-0.016*
	(0.039)	(0.025)	(0.052)	(0.052)	(0.038)	(0.017)	(0.026)	(0.010)	(0.021)	(0.009)
Casual / seasonal	0.022	0.068	-0.054	-0.115**	-0.073		-0.005	-0.005	0.039	-0.010
	(0.130)	(0.111)	(0.078)	(0.047)	(0.093)		(0.039)	(0.027)	(0.063)	(0.046)
Part-time	-0.022	-0.100	-0.266***	-0.120	-0.269***	-0.012	-0.025	0.001	-0.001	0.001
	(0.061)	(0.061)	(0.098)	(0.087)	(0.099)	(0.031)	(0.035)	(0.012)	(0.026)	(0.028)
Public sector	0.024	0.059**	0.075**	0.135***	0.132***	0.056***	0.044**	0.006	0.014	0.040***
	(0.023)	(0.024)	(0.033)	(0.030)	(0.030)	(0.015)	(0.021)	(0.007)	(0.014)	(0.011)
2nd level education	0.066**	-0.014	0.021	0.058*	0.031	0.001	0.056***	0.023***	0.003	0.041***
	(0.029)	(0.017)	(0.028)	(0.030)	(0.029)	(0.010)	(0.015)	(0.006)	(0.008)	(0.009)
3rd level education	0.080**	0.006	0.108***	0.081**	0.102***	0.005	0.066***	0.024***	-0.013	0.051***
	(0.038)	(0.016)	(0.023)	(0.034)	(0.035)	(0.013)	(0.018)	(0.008)	(0.010)	(0.010)
1st fifth of wage dist	-0.088***	-0.096***	-0.090***	0.023	-0.225***	-0.078***	-0.054**	-0.012	-0.005	-0.030**
	(0.026)	(0.023)	(0.033)	(0.031)	(0.039)	(0.016)	(0.024)	(0.008)	(0.011)	(0.014)
2nd fifth of wage dist	-0.074***	-0.057***	-0.093***	0.006	-0.157***	-0.038***	-0.048**	-0.020***	-0.007	-0.029**
	(0.021)	(0.020)	(0.028)	(0.030)	(0.033)	(0.013)	(0.019)	(0.007)	(0.010)	(0.012)
3rd fifth of wage dist	-0.076***	-0.028	-0.016	0.016	-0.133***	-0.028**	-0.015	0.000	0.008	-0.005
	(0.019)	(0.019)	(0.024)	(0.030)	(0.031)	(0.012)	(0.015)	(0.006)	(0.009)	(0.009)
4th fifth of wage dist	-0.030*	-0.012	0.018	0.019	-0.113***	-0.010	-0.011	-0.006	0.000	-0.001
	(0.017)	(0.016)	(0.021)	(0.025)	(0.025)	(0.010)	(0.011)	(0.005)	(0.009)	(0.008)
Estimated Rho [p-value]	0.380*** [0.000]	0.333*** [0.000]	0.411*** [0.000]	0.225*** [0.000]	0.318*** [0.000]	0.434*** [0.000]	0.388*** [0.000]	0.237*** [0.000]	0.246*** [0.000]	0.221*** [0.000]
Observations	4241	4091	5361	4478	3367	9695	3781	9338	8315	8274

Notes: Asterisks denote level of significance: * 10%, ** 5%, *** 1%. Other controls included but not reported are: dummies for married or cohabiting, health affects daily life, presence of children under 12, firm size in private sector, occupation , region, industry and year. Dummies were also included for cases where there were a very large number of missing values.

Table 3: RE Training Probits for Selected Variables (tenure omitted) - Marginal Effects (standard errors) for Women

Variable	Austria	Belgium	Britain	Denmark	Finland	France	Ireland	Italy	Netherlands	Spain
30-39 year old	0.038*	0.015	0.002	0.005	-0.050	-0.007	-0.015	0.017	0.000	-0.024
	(0.022)	(0.017)	(0.023)	(0.031)	(0.040)	(0.012)	(0.017)	(0.011)	(0.011)	(0.016)
40-49 year old	0.023	-0.016	-0.008	0.029	-0.048	-0.015	-0.020	0.023*	-0.007	-0.010
	(0.023)	(0.021)	(0.026)	(0.032)	(0.041)	(0.013)	(0.019)	(0.012)	(0.012)	(0.017)
50-54 year old	-0.037	-0.046	-0.030	0.042	-0.059	-0.039**	-0.021	0.022	-0.010	-0.029
	(0.036)	(0.031)	(0.032)	(0.040)	(0.047)	(0.019)	(0.029)	(0.015)	(0.017)	(0.024)
Fixed term contract	0.039	0.002	-0.015	-0.112***	-0.048*	0.035*	0.015	-0.016	-0.011	-0.006
	(0.030)	(0.022)	(0.044)	(0.039)	(0.029)	(0.018)	(0.026)	(0.015)	(0.025)	(0.014)
Casual / seasonal		-0.054	-0.056	-0.255***	-0.165		-0.041		-0.066	0.008
		(0.095)	(0.055)	(0.071)	(0.120)		(0.036)		(0.065)	(0.050)
Part-time	-0.025	-0.025	-0.109***	-0.049	-0.153***	-0.023	0.018	-0.011	-0.019*	0.011
	(0.023)	(0.019)	(0.028)	(0.036)	(0.056)	(0.017)	(0.020)	(0.010)	(0.011)	(0.023)
Public sector	0.008	0.055***	0.166***	0.040	0.127***	0.036**	0.020	0.027**	0.023*	0.032*
	(0.022)	(0.019)	(0.029)	(0.034)	(0.031)	(0.016)	(0.022)	(0.011)	(0.013)	(0.017)
2nd level education	0.045*	0.009	0.096***	0.094***	0.038	0.013	0.006	0.032***	0.020*	0.040**
	(0.026)	(0.022)	(0.028)	(0.033)	(0.033)	(0.013)	(0.021)	(0.010)	(0.012)	(0.018)
3rd level education	0.017	0.021	0.122***	0.126***	0.077**	0.044***	0.037	0.044***	0.041***	0.054***
	(0.036)	(0.020)	(0.023)	(0.035)	(0.035)	(0.015)	(0.024)	(0.013)	(0.015)	(0.019)
1st fifth of wage dist	-0.098***	-0.027	-0.110***	-0.125***	-0.142***	-0.054***	-0.045	-0.019	0.029*	-0.024
	(0.028)	(0.022)	(0.034)	(0.040)	(0.044)	(0.018)	(0.030)	(0.013)	(0.017)	(0.025)
2nd fifth of wage dist	-0.071***	0.022	-0.032	-0.050	-0.066	-0.038**	-0.016	-0.016	0.040**	-0.021
	(0.026)	(0.019)	(0.031)	(0.038)	(0.041)	(0.017)	(0.026)	(0.011)	(0.017)	(0.021)
3rd fifth of wage dist	0.007	0.016	0.001	-0.068*	-0.060	-0.029*	0.001	-0.015	0.022	-0.020
	(0.022)	(0.019)	(0.030)	(0.035)	(0.039)	(0.015)	(0.022)	(0.010)	(0.016)	(0.018)
4th fifth of wage dist	-0.013	-0.006	0.042	-0.001	-0.006	-0.017	0.016	-0.009	0.010	0.000
	(0.021)	(0.017)	(0.028)	(0.033)	(0.038)	(0.013)	(0.021)	(0.009)	(0.016)	(0.014)
Estimated Rho [p-value]	0.398*** [0.000]	0.286*** [0.000]	0.397*** [0.000]	0.267*** [0.000]	0.296*** [0.000]	0.453*** [0.000]	0.326*** [0.000]	0.254*** [0.000]	0.138*** [0.000]	0.288*** [0.000]
Observations	2834	3322	5331	4157	3420	7871	2664	6161	4966	4390

Notes: See notes to Table 2.

Table 4: Predicted Average Probability of Training (standard error)

Country	Characteristics	Coefficients	
		Male	Female
Austria	**Male**	0.142 (0.005)	0.121 (0.009)
	Female	0.151 (0.009)	0.135 (0.006)
Belgium	**Male**	0.112 (0.005)	0.102 (0.006)
	Female	0.093 (0.006)	0.107 (0.005)
Britain	**Male**	0.405 (0.006)	0.411 (0.011)
	Female	0.381 (0.013)	0.423 (0.006)
Denmark	**Male**	0.437 (0.006)	0.436 (0.013)
	Female	0.517 (0.012)	0.473 (0..007)
Finland	**Male**	0.356 (0.007)	0.378 (0.014)
	Female	0.365 (0.013)	0.421 (0.007)
France	**Male**	0.111 (0.003)	0.096 (0.005)
	Female	0.112 (0.004)	0.118 (0.004)
Ireland	**Male**	0.069 (0.004)	0.081 (0.007)
	Female	0.072 (0.006)	0.077 (0.005)
Italy	**Male**	0.042 (0.002)	0.045 (0.003)
	Female	0.066 (0.004)	0.072 (0.003)
Netherlands	**Male**	0.050 (0.002)	0.061 (0.005)
	Female	0.055 (0.004)	0.065 (0.003)
Spain	**Male**	0.078 (0.003)	0.065 (0.004)
	Female	0.108 (0.004)	0.104 (0.004)

Notes: (i) The predicted probabilities are calculated as the average of predicted probabilities over gender using estimated models with tenure omitted. See text for further details.

(ii) The standard errors are calculated as the square root of $\frac{\partial \hat{P}}{\partial \hat{\beta}'}[c\hat{o}v(\hat{\beta})]\frac{\partial \hat{P}}{\partial \hat{\beta}} + \frac{1}{n^2}\Sigma\left(\hat{p}_i - \hat{P}\right)^2$ where $\hat{\beta}$ are the logit model coefficient estimates, $c\hat{o}v(\hat{\beta})$ is the estimated variance covariance matrix, $\hat{P}$ = (1/n) $\sum \hat{p}_i$ $\hat{p}_i$ is the predicted probability of starting a training event, and n is the total number of observations used in the summation. See Gomulka and Stern (1990) for further details about the derivation of this formula.

Appendix

Table A.1: Means of key variables

		Austria	Belgium	Britain	Denmark	Finland	France	Ireland	Italy	Netherlands	Spain
Fixed-term contract	Men	0.034	0.051	0.017	0.032	0.085	0.054	0.022	0.040	0.018	0.220
	Women	0.046	0.092	0.029	0.047	0.128	0.059	0.044	0.045	0.033	0.222
Casual / seasonal	Men	0.005	0.002	0.008	0.050	0.012	0.000	0.026	0.016	0.001	0.008
	Women	0.000	0.006	0.018	0.020	0.010	0.000	0.069	0.017	0.009	0.028
Part time	Men	0.017	0.022	0.013	0.015	0.021	0.041	0.044	0.036	0.030	0.018
	Women	0.269	0.247	0.290	0.158	0.067	0.197	0.281	0.211	0.439	0.130
Public sector	Men	0.257	0.322	0.219	0.301	0.313	0.409	0.374	0.343	0.235	0.253
	Women	0.326	0.428	0.407	0.591	0.540	0.553	0.393	0.470	0.383	0.395
Education ISCED 0-2	Men	0.121	0.249	0.395	0.147	0.184	0.244	0.325	0.445	0.157	0.494
	Women	0.216	0.165	0.522	0.141	0.186	0.235	0.225	0.326	0.182	0.329
Education ISCED 3	Men	0.796	0.344	0.143	0.451	0.455	0.467	0.410	0.438	0.590	0.206
	Women	0.682	0.268	0.140	0.401	0.339	0.393	0.509	0.540	0.549	0.228
Education ISCED 5-7	Men	0.083	0.346	0.459	0.401	0.361	0.258	0.260	0.113	0.243	0.300
	Women	0.102	0.507	0.336	0.458	0.475	0.344	0.262	0.132	0.263	0.443
Bottom fifth of wage dist	Men	0.110	0.178	0.104	0.170	0.161	0.143	0.124	0.163	0.165	0.159
	Women	0.335	0.261	0.281	0.262	0.283	0.223	0.275	0.244	0.275	0.215
Second fifth of wage dist	Men	0.202	0.205	0.172	0.175	0.177	0.183	0.177	0.203	0.184	0.195
	Women	0.223	0.208	0.219	0.204	0.256	0.188	0.214	0.204	0.243	0.195
Third fifth of wage dist	Men	0.216	0.214	0.192	0.165	0.182	0.203	0.220	0.207	0.194	0.203
	Women	0.167	0.180	0.201	0.245	0.207	0.207	0.182	0.197	0.215	0.193
Fourth fifth of wage dist	Men	0.230	0.190	0.244	0.215	0.229	0.224	0.256	0.214	0.205	0.215
	Women	0.158	0.196	0.165	0.184	0.152	0.204	0.175	0.170	0.176	0.188
Top fifth of wage dist	Men	0.242	0.213	0.288	0.275	0.250	0.247	0.222	0.213	0.251	0.228
	Women	0.116	0.155	0.134	0.105	0.102	0.178	0.154	0.186	0.090	0.209

Note: estimates are weighted.

Table A.2: Training Participation Ratios in Europe, Disaggregated across Key Variables

	Austria	Belgium	Britain	Denmark	Finland	France	Ireland	Italy	Netherlands	Spain
Incidence of training starts										
(1) All	0.16 (4)	0.14(6)	0.41 (2)	0.42 (1)	0.34 (3)	0.15 (5)	0.09 (8)	0.06 (10)	0.07 (9)	0.10 (7)
(2) Men	0.16 (4)	0.14 (6)	0.41 (2)	0.42 (1)	0.34 (3)	0.15 (5)	0.09 (8)	0.06 (10)	0.07 (9)	0.10 (7)
(3) Women	0.16 (4)	0.13 (5)	0.43 (2)	0.47 (1)	0.41 (3)	0.16 (4)	0.10 (7)	0.09 (8)	0.08 (9)	0.12 (6)
Ratios of training starts										
(4) Women to men	0.96 (9)	0.95 (10)	1.04 (8)	1.10 (5)	1.20 (3)	1.07 (6)	1.12 (4)	1.61 (1)	1.06 (7)	1.30 (2)
(5) Young (25-29) to Old (50+)										
Men	1.51 (3)	1.25 (4)	1.20 (5)	1.03 (7)	1.17 (6)	1.96 (2)	0.89 (10)	0.91 (9)	4.19 (1)	1.01 (8)
Women	1.71 (2)	1.64 (3)	1.02 (7)	0.88 (9)	0.96 (8)	1.57 (4)	1.96 (1)	0.45 (10)	1.55 (5)	1.25 (6)
(6) Fixed-term to permanent										
Men	0.48 (9)	0.76 (6)	0.77 (5)	0.98 (3)	0.69 (8)	1.06 (2)	0.75 (7)	0.81 (4)	1.33 (1)	0.31 (10)
Women	0.87 (6)	1.14 (3)	1.11 (4)	0.83 (7)	0.89 (5)	0.77 (8)	1.37 (1)	0.74 (9)	1.26 (2)	0.77 (8)
(7) Public to private sector										
Men	1.26 (8)	1.35 (7)	1.35 (6)	1.40 (5)	1.50 (4)	1.14 (9)	2.01 (1)	1.61 (3)	0.82 (10)	1.79 (2)
Women	1.57 (5)	1.37 (6)	1.73 (4)	1.19 (8)	1.32 (7)	1.17 (9)	2.17 (2)	4.18 (1)	1.02 (10)	2.15 (3)
(8) Education ISCED 0-2 to 5-7										
Men	0.17 (9)	0.37 (6)	0.57 (2)	0.48 (4)	0.47 (5)	0.49 (3)	0.18 (8)	0.17 (9)	0.94 (1)	0.24 (7)
Women	0.26 (6)	0.24 (8)	0.54 (3)	0.47 (4)	0.60 (2)	0.42 (5)	0.25 (7)	0.11 (9)	0.65 (1)	0.25 (7)
(9) Bottom to top fifth of wages										
Men	0.30 (6)	0.30 (6)	0.43 (3)	0.60 (2)	0.39 (4)	0.33 (5)	0.15 (9)	0.20 (7)	1.31 (1)	0.16 (8)
Women	0.19 (8)	0.37 (5)	0.47 (4)	0.50 (3)	0.50 (3)	0.53 (2)	0.20 (7)	0.15 (9)	1.17 (1)	0.25 (6)
(10) Part-time to full-time										
Men	1.22 (3)	0.45 (9)	0.57 (8)	0.74 (6)	0.29 (10)	0.78 (5)	0.85 (4)	1.99 (1)	0.64 (7)	1.36 (2)
Women	0.65 (10)	0.69 (7)	0.65 (9)	0.82 (3)	0.67 (8)	0.77 (4)	0.91 (2)	1.53 (1)	0.69 (6)	0.74 (5)

Notes: Education is categorised according to the International Standard Classification of Education (ISCED). Levels 0-2 cover less than upper secondary education, level 3 is upper secondary education (e.g. GCE A-levels, baccalaureat) and levels 5-7 cover tertiary education, both university and non-university. Cross-country ranks are in parentheses. Estimates are weighted.