Are there Asymmetries in the Effects of Training on the Conditional Male Wage Distribution?

by

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Abstract

We use a quantile regression framework to investigate the degree to which work-related training affects the location, scale and shape of the conditional wage distribution. Human capital theory suggests that the percentage returns to training investments will be the same across the conditional wage distribution. Other theories – whether based on imperfections in the labour market or on skill-mix heterogeneity – suggest that this need not be the case. Using the first six waves of the European Community Household Panel, we investigate these issues for private sector men in ten European Union countries. Our results show that, for the vast majority of countries, investment in training yields similar percentage returns across the conditional wage distribution. Only Belgium was an outlier in this respect. However, our results do indicate that there are considerable differences in *mean returns* to training across countries.

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1. INTRODUCTION

The mean returns to various forms of human capital have been extensively investigated in the labour economics literature, especially the returns to formal education and work-related training. Relatively recently, attention has shifted to investigating the degree to which education might be associated with more complex changes in the conditional wage distribution, and what these associations say about movements in wage inequality and differing returns to education.[1] In this paper we utilize the quantile regression (QR) framework to investigate the extent to which private sector training affects the location, scale and shape of the conditional wage distribution, and investigate whether or not these patterns are consistent with various alternative models of training investment and labour market structures. Using the first six waves of the European Community Household Panel (ECHP), we carry out this analysis for private sector men in ten European Union countries.[2]

There are a number of economic variables that are not typically available in micro data sets but that can affect wages. Examples are unobserved 'ability', unmeasured components of human capital formation such as informal training giving rise to productivity differences, and labour market structures like monopsony. They can explain why there is still a wide dispersion of wages even after conditioning on a range of observable human capital characteristics. For example, in our analysis, we condition on the initial wage and a set of other firm-specific, job-specific and personal characteristics including accumulated training. We hypothesise that the dispersion of conditional wages is caused by differing rates of unmeasured, informal skill accumulation; differences in the specific-general mix of these skills; individual-specific productivity; and differing market structures. In contrast to

1 For surveys of studies estimating the mean returns to education and training, see Ashenfelter and Card (2001) and Ashenfelter and RJ Lalonde (1996). Studies estimating the returns to education using quantile regression techniques include Arias, Hallock and Sosa-Escudero (2001) and Gonzales and Miles (2001).

2 To our knowledge there are no studies investigating how training affects the conditional wage distribution, although there has been a recent surge in the estimation of wage equations using quantile regression techniques (see Fitzenberger, *et al,* 2001, for some applications of quantile regression techniques.

conventional ordinary least squares (OLS) techniques, QR methods allow for flexible interactions between these unobservable factors and observable wage determinants. If the observed determinants of wages, such as training, interact with the unobservables in a non-trivial way – for example, if monopsony affects the returns to training – then an exogenous shift in training may affect the scale and shape, as well as the location, of the conditional distribution.[3] [4] While OLS allows a locational shift only, QR provides a fuller view of these effects. We now discuss some reasons why we may or may not expect human capital effects to differ across the conditional wage distribution.

In a perfectly competitive labour market, there are good reasons to expect that percentage returns to investment in similar forms of human capital might be the same across the conditional wage distribution.. If capital and labour markets function according to the competitive paradigm and if human capital is general, then any individual investment in human capital should yield equal percentage returns across the conditional wage distribution. However, there are several arguments suggesting that this might not be the case.

First, if there are significant complementarities between unobservable ability and education, then higher ability individuals – further to the right in the conditional wage distribution – might have higher returns to education. This has been found in a study by Arias, Hallock and Sosa-Escudero, 2001. If this argument also applies to work-related

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3 In order to difference out the effects of unobserved individual effects in standard linear panel data models it is assumed that they enter the equation additively. In contrast, here we assume that the unobservables enter via interactions with the other covariates. As in the standard linear panel data model, the assumption that the overall equation error is uncorrelated with unobserved heterogeneity and included covariates is maintained here.

4 Quantile regression allows identification of the returns to training in the sense that it provides a picture of how the conditional distribution varies with training. For example, a positive coefficient on the training variable in a 10th percentile regression would indicate that an increment of training is associated with an upward movement in the 10th percentile of the conditional wage distribution. This coefficient, which is the derivative of the conditional quantile function, is the estimated return. The models we sketch out in the text imply certain patterns of estimated returns, and we test whether the data are consistent with these. Without such priors it is difficult to make inferences about the wages of given individuals based on QR coefficients (for example, one cannot say whether an individual at the 10th percentile in the absence of training would remain at the 10th percentile if they received training).

training, there will be an upward sloping profile when we graph the training effect across quantiles of the conditional wage distribution, because of ability (an unobservable individual-specific effect that may interact with training differentially across the conditional wage distribution).

Second, any variations in the returns to training across the conditional wage distribution might reflect heterogeneity in the mix of skills that are embodied in training. In particular, as suggested by Stevens (1994) and Lazear (2003), some firms might offer skills packages – comprising both formal and informal training – that are more specific than others. Training that is specific and partially firm-financed will produce lower individual wage returns than self-financed general training. We can measure the more formal types with our training measure and on-the-job training with our tenure measure. But, as noted above, there may still be some types of informal training that we are unable to capture with our controls and a heterogeneous specific-general mix will add to the conditional dispersion of wages. If there are complementarities between formal and informal training, we would find that the estimated formal training effects on wages should increase as we move up the conditional wage distribution. Workers to the left of the conditional wage distribution will be those who have received training that is specific and partially firm-financed. Those to the right may have received general training. But here the reason will be due to unobservable *firm-specific* effects rather than individual-specific effects.

Third, if the labour market is not everywhere perfectly competitive, there could also be varying returns to training across the conditional wage distribution. A number of recent papers suggest that labour market imperfections might lead firms to finance general training (Stevens, 1994; Acemoglu and Piscke, 1999; Booth and Zoega, 1999). This will be the case wherever a worker's productivity is increasing at a faster rate than wages. To the extent that this 'wedge' is unobservable in survey data, we might expect to see variations from the average returns to training across different quantiles of the conditional wage distribution. These will reflect unobservable differences in the degree of imperfect competition and in the extent to which firms have financed individuals' training and are reaping the returns.

For example, workers subject to greater monopsony power will have lower than expected wages, and the firm will take a larger share of the returns to any training. Therefore, the estimated training effects on wages should increase as we move up the conditional wage distribution. Intuitively this is because by definition monopsony power is associated with lower wages. As this power declines, not only will trained workers finance more of their training and thus reap greater returns, but untrained workers will be paid more as monopsony power declines and we move up the conditional wage distribution. However, such effects might not appear as unobservable, since imperfect competition in the labour market might by proxied by industry dummies. Moreover, since we are analysing men, the usual monopsony arguments - that are arguably more likely to apply to women constrained by family circumstances - may not be relevant, although Manning (2003) suggests otherwise.

Finally, some firms – for instance those with better human resource management - might simply offer better quality work-related training than other firms as well as pay higher wages. Workers to the left of the conditional wage distribution will be those in the lower quality firms and that is why both training returns and the untrained wage are lower. Those to the right are in the better quality firms. In this case there will be again be an upward sloping profile when we graph the training effect across quantiles of the conditional wage distribution and here the reason will also be unobservable firm-specific effects.

These various hypotheses are hard to test with available data. Ideally we would like linked employer-employee data in order to control for individual- and firm-specific unobservable and observable effects.[5] However, in this paper we take a first step towards

[5] However, even this type of data will typically not have information on productivity.

investigating these issues by analysing the impact of work-related training on the conditional wage distribution using QR techniques for a sample of individual-level data. A related goal is to see how these training effects differ across European Union (EU) countries.[6]

2. THE ECONOMETRIC MODEL

There is now an extensive literature that estimates the impact of training on expected wages using a linear regression framework (see *inter alia* references in Ashenfelter and Lalonde, 1996; and Arulampalam and Booth, 2001). Here, we deviate from this common practice by looking at the effects of training and other covariates on different quantiles of the log wage distribution.[7] The main advantage of a quantile regression (QR) framework is that it enables one to model the effects of the covariates on the location, scale and shape of the conditional wage distribution, unlike the linear regression model (least squares) that only allows one to look at the effect on the location (the conditional mean).

Training receipts can have a cumulative effect on wages. Since we do not have the entire history of training receipts for individuals in our sample, we include the wage from wave 1 as an additional regressor in the QR framework in order to take into account the role played by the past training receipts in the accumulation of additional human capital.[8] This also enables us to control for possible time-invariant individual specific unobservable effects in this framework.[9]

[6] There is an extensive literature on the evaluation of particular labour market programmes, using a variety of techniques. For example, see Heckman *et al.* (1994) look at the average effects of training on the treated, Heckman *et al* (1997) look at the distribution of treatment effects using a non instrumental variable (IV) framework, and Abadie *et al* (2002) look at training effect on different quantiles of the wage distribution using the IV framework. The variable of interest here is employer provided training and not a labour market program and thus we do not treat training as endogenous here.

[7] The linear conditional quantile regression model was first introduced by Koenker and Bassett (1978). For a recent survey of these models, see Buchinsky (1998).

[8] There is no information on the complete history of training received by individuals in the sample. All we observe is whether or not an individual receives an additional training event at each wave.

[9] In simple panel data models concerned with estimating the effect of training on conditional mean wage, it is customary to either first difference the equation prior to estimation or to use within-group deviations to account for individual specific unobservables. This route is not open to us, since the difference of the wage

We specify the θth ($0<\theta<1$)[10] conditional quantile of the log wage (w) distribution for the i-th individual ($i=1,.., n$) in wave t ($t=2,..,T_i$) as

$$\text{Quant}_\theta(w_{it}|\mathbf{x}_{it}, D_{it}, w_{i1}) = \alpha(\theta) + \mathbf{x}_{it}'\beta(\theta) + D_{it}\,\gamma(\theta) + \delta(\theta)\, w_{i1} \qquad (1)$$

implying

$$w_{it} = \alpha(\theta) + \mathbf{x}_{it}'\beta(\theta) + D_{it}\,\gamma(\theta) + \delta(\theta)\, w_{i1} + u_{\theta it} \qquad (2)$$

with $\text{Quant}_\theta(u_{\theta it}|\mathbf{x}_{it}, D_{it}, w_{i1}) = 0$.

In the above specifications, (i) w_{i1} is the log wage from wave 1 which is included to take into account the initial conditions as discussed above, (ii) D_{it} is the cumulative count of *completed* courses since the first wave of the sample and therefore increases by one every year when there the individual is in receipt of training between the two waves. This model is estimated on the pooled sample of men. Because of the definition of the training variable used in the model, individuals stay in the sample continuously until they fail to give an interview, which results in an unbalanced panel with different individuals contributing different numbers of observations.

Note that, if the underlying model were truly a location model - in the sense that the changes in explanatory variables causing only a change in the location of the distribution of w and not in the shape of the distribution - then all the slope coefficients would be the same for all θ.[11]

We use Stata 8 to estimate the coefficients of our QR model. The standard errors are calculated using the bootstrap method using 500 replications.

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quantile is not the same as the quantile of the differenced wage.

[10] $\theta=0.5$ refers to the Median.

[11] Quantile regression models are more general than simple linear regression model allowing for heteroskedastic errors, since the QR model allows for more general dependence of the distribution of w (the dependent variable) on the **x**s instead of just the mean and the variance alone.

3. 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. However, we 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, as explained in Booth and Bryan (2002).

In earlier work using the ECHP, we found that training incidence is typically significantly higher in the EU public sector than the private (Arulampalam, Booth and Bryan, 2003). This finding came as no surprise, since private sector firms are more likely than the public sector to be constrained by the need to make profits, and so they may be less willing to finance training through fears of losing trained workers to rival non-training firms (Booth, 1991). Since various theories about human capital acquisition and its impact on earnings have been formulated with private-sector profit maximisation in mind, we focus only on the private sector in this study.[12] We also consider only men, although in a subsequent study we investigate the gender wage gap using QR techniques and the ECHP data.[13]

We wish to avoid conflating work-related or 'continuing training' with initial vocational education or training.[14] We therefore exclude from our analysis individuals under

[12] Moreover, our preliminary testing showed that it is inappropriate to pool private and public sector workers since the coefficients across the sub-groups differ significantly, as might be expected given that public and private sector employers typically have different objective functions.

[13] The reason we focus only on men is that we wish to avoid selectivity issues that we would need to address when investigating women. Consequently we are able to concentrate in this study on a careful and thorough investigation of private sector male wages that will inform our subsequent analysis.

[14] Despite the harmonisation of the ECHP, what respondents report as training may depend partly on the very heterogeneous country-specific vocational training and education systems. However, cross-country comparisons of continuing training – the measure we use in our analysis - are likely to be more robust for two reasons. First, there is typically much less regulation of continuing training than initial 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.

the age of 25 years, paid apprentices, and those on special employment-related training schemes.[15]

For each country, our estimating sub-sample comprises employed private sector men who are: (i) between the ages of 25 and 54 years and working at least 15 hours per week; (ii) not employed in agriculture; (iii) employed in the private sector; and (iv) with valid observations on all the variables used in the wage equations; and (v) with sequences of continuous observations starting from the first wave in the sample in order to have a complete training record (see also Data Appendix). Individuals can be present for a minimum of two waves (including the first wave) and a maximum of six waves for all countries except for Austria and Britain (where the maximum is five) and Finland (where the maximum is four).[16]

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 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 these represent only a tiny fraction of male workers).[17] We include in our analysis the ten European countries listed in Table 1 and estimate the models using pooled person-year observations.[18]

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15 Apprentices and those on special training schemes account for only 1.1% of the sampled age group.

16 Because we need a complete record of training for each individual, we drop any observations, which follow a break in the data. Therefore, if an individual is observed in waves 1, 2, 3, 5 and 6, we use waves 1, 2 and 3 only.

17 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%.

18 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.

The dependent variable is the log of the average hourly wage, including overtime payments, in the respondent's main job.[19] The characteristics of each country's unconditional log wage distribution, deflated to 1999 prices, are reported in Table 1. The deflators are the European Union's harmonised indices of consumer prices (HICP; see *Eurostat Yearbook,* 2002). To facilitate cross-country comparisons of consumption wages, the log wage figures were converted to purchasing power parity (PPP) units, using the scaling factors supplied with the ECHP. The first column shows substantial variation in mean wages across countries, from a high of 2.7 log points in the Netherlands down to 2.1 log points in Spain (with 2.2 log points in Italy). But there are also differences in the dispersion of wages, as shown by the standard deviations in the second column. By this measure, the country with the lowest dispersion (0.031) is Denmark (which has the second highest mean wage, 2.69 log points), whilst Ireland has the highest dispersion (0.52). It is notable that Spain has the lowest mean and one of the highest standard deviations, 0.51. The remaining columns show the median, the 10th and 90th percentiles, and in the last column the difference between the 90th and the 10th percentiles. This measure of dispersion shows a similar pattern to the standard deviation: Britain, Ireland and Spain stand out as countries with high hourly wage dispersion.

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 start and end dates of the course to identify distinct training events.[20] We then construct our

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[19] The log wage was calculated from the ECHP variables as log (wage) = log (PI211MG * (12/52) / PE005A) = log (normal gross monthly earnings from main job including overtime * (12/52) / hours in main job including overtime). No specific information is provided on overtime hours and premia.

[20] 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,

training variable D_{it} as the cumulative count of *completed* courses since the first wave of the sample. Most studies simply examine the impact of training incidence (and sometimes intensity) on wages, but not the number of events.[21] We follow Lillard and Tan (1992) in using the accumulated sum of all training events, where there is only one event measured at each wave owing to the nature of our data.

The framing of the training question suggests that the training responses should be interpreted as more formal courses of instruction, rather than informal on-the-job training (for which we control – at least in part – using job tenure). 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.

Table 2 reports information about completed training courses for private sector men by country. The first column gives the number of observations for each country, while the second column reports the mean number of waves for each country.[22] The third column reports training incidence for completed courses only. For example, the first row of Table 2 shows that the Austrian sub-sample comprises 804 private sector men who are observed in three waves on average and of whom 15% have completed a training course in any year. The mean accumulated training count is simply the product of the second and third columns. The figures in the third column show that training incidence differs considerably across countries. We can identify three high-incidence countries – Britain, Denmark and Finland – where each year over 30% of individuals complete training courses. In contrast Austria,

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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.

21 Exceptions are Lillard and Tan (1992), Arulampalam, Booth and Elias, (1997), Blundell et al. (1999) Arulampalam and Booth (2001), and Booth and Bryan (2002). Lillard and Tan (1992: p31) note that multiple training occurrences within a period are typically not known from US survey data.

22 As explained earlier, individuals can be present for a minimum of two waves and a maximum of six waves for all countries except for Austria and Britain (where the maximum is five) and Finland (where the maximum is four).

Belgium and France form a group of medium-incidence countries, where each year between 10% and 15% of men complete training courses. Finally, Ireland, Italy, the Netherlands and Spain have incidence below 10%.

Though our sample is limited to men in the private sector, the cross-country pattern summarised in Table 2 is similar to that found in analysis of overall training (Arulampalam, Booth and Bryan, 2003). The ranking also compares reasonably well (especially for the high incidence countries) with the cross-country comparisons using different data sources reported in OECD (1999); and with International Adult Literacy Survey (IALS) data on continuing training for several countries featured in OECD (2003).

4. RESULTS

4.1 Returns to Training

Table 3 reports the quantile regression estimates for the returns to training (the derivative of the conditional quantile or mean wage with respect to training), as measured by the coefficient on the training receipt dummy, for five different values of θ (0.1, 0.25, 0.5, 0.75 and 0.90). The other controls are human capital, demographic and job characteristics expected to affect earnings. We include dummy variables for age and job tenure bands, any unemployment experienced since 1989, marital status, health problems affecting daily life, highest educational levels, fixed term or casual employment, part-time work, establishment size, one-digit occupation and industry, year and, where the data allow, region. We also include a separate control for training started in the current year but uncompleted at the survey date. Dummies were also included for cases where there were a very large number of missing values (see Data Appendix). To facilitate comparison with the usual procedure, which estimates the impact of training on the expected wage, we report the ordinary least squares (OLS) estimates in the first column of Table 3. In Figure 1 we also present the estimated returns for each of the quantiles of the log wage distribution along with the 95% confidence band around the estimates. Superimposed on the plots is a dotted horizontal line representing the OLS estimate of the effect of training on expected log wages.

Table 3 reveals an interesting pattern of estimated returns to training. The estimated returns to the expected wage (the OLS results) vary from the highest, of around 5.9% in Ireland, to the lowest and statistically insignificant returns in Belgium and Italy. We next turn to the QR estimates of the returns to training. As noted earlier, if it is found that investment in training yields similar percentage returns across the conditional wage distribution, this would imply that training only has an effect on the location of this conditional wage distribution.

Inspection of the returns to training at different quantiles of the conditional wage distribution is more illuminating than the simple OLS estimation. For example, France and Ireland are the only countries where the estimated returns to training are significantly different from zero at all quantiles, with Ireland enjoying much larger returns compared to France. Unlike OLS, QR estimates are robust to outliers. This is clearly brought out in the estimates for Netherlands where the return to the conditional mean wage is about 3% and significant, whilst the QR estimates reveal that the returns are insignificant in all quantiles. In this case the significance found in OLS results is entirely driven by a small group of outliers. If the 0.5% of observations with the highest and lowest residuals are excluded, the coefficient falls to 0.008 with a standard error of 0.006, very similar to the median estimates. Returns to training in Italy are insignificant at all quantiles and in Belgium there is a significant 2.4% returns estimated at the 0.25^{th} quantile. Interestingly, we find training to increase the dispersion of the conditional wage distribution in Austria, *ceteris paribus*. A broadly similar result was found for Britain.

Homogeneity in returns to training would imply that the figures are flat so that it is possible to draw a horizontal line within the confidence interval band. Inspection of the plots in Figure 1 and the estimates in Table 3 reveals that, in all countries apart from Belgium, the conditional distribution of wages with training is no more dispersed than in the case without training. This is also confirmed by the test of equality of (returns to training) coefficients at the 0.10, 0.25, 0.50, 0.75 and 0.90 quantiles presented in Table 4. For Belgium the F-statistic implies a rejection of this equality hypothesis at the 5% level ($F(4,1760)=2.78$), whereas in the other countries one cannot reject equality at conventional significance levels. The remaining F statistics are from pair-wise equality tests. As expected, in Belgium several of these statistics imply a strong rejection of pair-wise equality. But there is also some evidence of rejection of pair-wise equality in two of the other countries, France and Ireland, as inspection of Tables 3 and 4 makes clear.

We noted earlier that, in a perfectly competitive labour market, there are good reasons to expect that percentage returns to investment in general training might be the same across the conditional wage distribution for workers of identical ability. Our QR estimates summarised in Table 3 and Figure 1 show that, for the vast majority of our countries, there is no statistically significant difference between the conditional distributions for those with training compared to those without.

As noted earlier, if there are significant complementarities between unobservable productivity and work-related training, then higher productivity individuals – further to the right in the conditional wage distribution – should have higher returns to training. Yet this is found in our data only for Austria and Britain, as illustrated in Figure 1, where the effects are not, however, significantly different from each other across the conditional wage distribution. Indeed, the only country with a significant effect is Belgium, where the reverse is found – individuals further to the left in the conditional distribution have higher returns to training - suggesting that unobservable productivity and work-related training are not complements.

As noted in the introduction, some recent papers argue that imperfect competition in the labour market might lead firms to finance general training provided a worker's productivity is increasing in training more quickly than wages. To the extent this 'wedge' is unobservable in survey data, then we would expect to see variations from the average returns to training across different quantiles of the conditional wage distribution, reflecting variations in wages due to monopsony power and the degree to which firms have financed such training and are reaping the returns. For example, workers subject to greater monopsony power may have lower than expected wages, and the firm will take a larger share of the returns to any training. Therefore, the estimated training effects on wages should increase as we move up the conditional wage distribution.

Moreover, if some firms offer skills packages that are more specific than others, we would also expect variations in individual returns across the conditional wage distribution reflecting unobservable skill specificity in both formal and informal training. Yet in our estimates we observe remarkably little heterogeneity in returns across the conditional distribution for each country.

While our results may be consistent with the hypothesis that, in a perfectly competitive labour market, percentage returns to investment in general training will be the same across the conditional wage distribution, we believe that it is hard to argue that European labour markets fit the competitive paradigm. An alternative interpretation is that the effects of firm-specific and individual-specific unobservables wash out, and that their net effect is therefore uniform across the conditional wage distribution. Variations in skill-mix (from specific to general) and in labour market imperfections, coupled with unobserved individual-specific productivity, most likely contribute to our finding of no consistent pattern across the conditional wage distribution.

In summary, our results for the training effect suggest that the way in which unobservables interact with training receipts is fairly uniform across the conditional wage distribution within a country. Moreover, this finding was repeated for the vast majority of the EU countries we investigated. Only Belgium was an outlier in this respect. This is an interesting result, and one that is counter to the results found for education in other studies - and in our own - and we return to this issue in the next sub-section. However, our results do suggest that there are considerable differences in *mean returns* to training across countries, and it is to these estimates that we now turn.

The OLS estimates of the mean returns to each completed training event are given in the first column of Table 3. The three countries with the highest training incidence – Britain, Denmark and Finland – are also amongst the countries with the lowest returns, of approximately one percent per event. Ireland has by far the highest mean returns (nearly 6 percent) to each completed training event, followed by France, Spain and Austria, all of whom have statistically significant returns to each event of over 2 percent. For Belgium, however, it is more appropriate to use the QR estimates, since returns to training across the various quantiles of the Belgian conditional wage distribution are significantly different from each other. The Netherlands is a special case, since as noted earlier, the significant mean return found is entirely driven by outliers.

4.2 Returns to Education

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 dummy variables Educ2 and Educ3 refer to the ISCED-Level 3 and ISCED-levels-5-7 respectively.[23]

We report the results for the estimated returns to education in Table 5. In all cases, as expected, there are positive returns to education: accumulation of human capital via education shifts the wage distribution to the right, *ceteris paribus*. In addition, our QR estimates show that the conditional distribution differs for educated individuals compared to the less educated. This finding is consistent with the idea that there are complementarities between unobservable ability (or productivity) and education, since higher ability individuals – further to the right in the conditional wage distribution – have higher returns to education. This result is found for the vast majority of our countries and for both 2nd and 3rd levels of higher levels of education.

5. CONCLUSIONS

In this paper we used quantile regression techniques to investigate the degree to which work-related training affects the location, scale and shape of the conditional wage distribution. Human capital theory suggests that the percentage returns to training investments will be the same across the conditional wage distribution. Other theories – whether based on imperfections in the labour market or on skill-mix heterogeneity – suggest that this need not be the case. Using the first six waves of the European Community Household Panel, we investigated these issues for private sector men in ten European Union countries. Our results for training suggest that, for the vast majority of countries, investment in training yields similar percentage returns across the conditional wage distribution. In other words, the way unobservables interact with training receipts appears fairly uniform across the conditional wage distribution. Only Belgium was an outlier in this respect.

[23] ISCED-level-4 is not separately identified in this dataset.

While this finding is consistent with orthodox general human capital theory, which assumes a perfectly competitive labour market for workers of identical unobservable productivity, we believe it is hard to argue that European labour markets fit the competitive paradigm. An alternative interpretation is that the effects of firm-specific and individual-specific unobservables wash out, and that their net effect is therefore uniform across the conditional wage distribution. Variations in skill-mix (from specific to general) and in labour market imperfections, coupled with unobserved individual-specific productivity, most likely contribute to our finding of no consistent pattern across the conditional wage distribution.

However, our results do suggest that there are considerable differences in *mean returns* to training across countries. The three countries with the highest training incidence – Britain, Denmark and Finland – are also amongst the countries with the lowest returns, of approximately one percent per event. Ireland has by far the highest mean returns (nearly 6 percent) to each completed training event, followed by France, Spain and Austria, all of whom have statistically significant returns to each event of over 2 percent. Belgium is the only country for which it is more appropriate to use the QR estimates, since returns to training across the various quantiles of the Belgian conditional wage distribution are significantly different from each other.

We also find that there are positive returns to education and that education shifts the wage distribution to the right. In addition, the returns at the upper parts of the distribution are much higher than at the lower parts of the distribution, implying that education also increases wage dispersion. This finding is consistent with the idea that there are complementarities between unobservable ability (or productivity) and education, since higher ability individuals – further to the right in the conditional wage distribution – have higher returns to education.

Our QR estimates of the training returns across the conditional wage distribution offer an interesting way forward. In future work it would be interesting to estimate these models using linked employer-employee data in order to ascertain the relative importance of firm-specific and individual specific unobservables.

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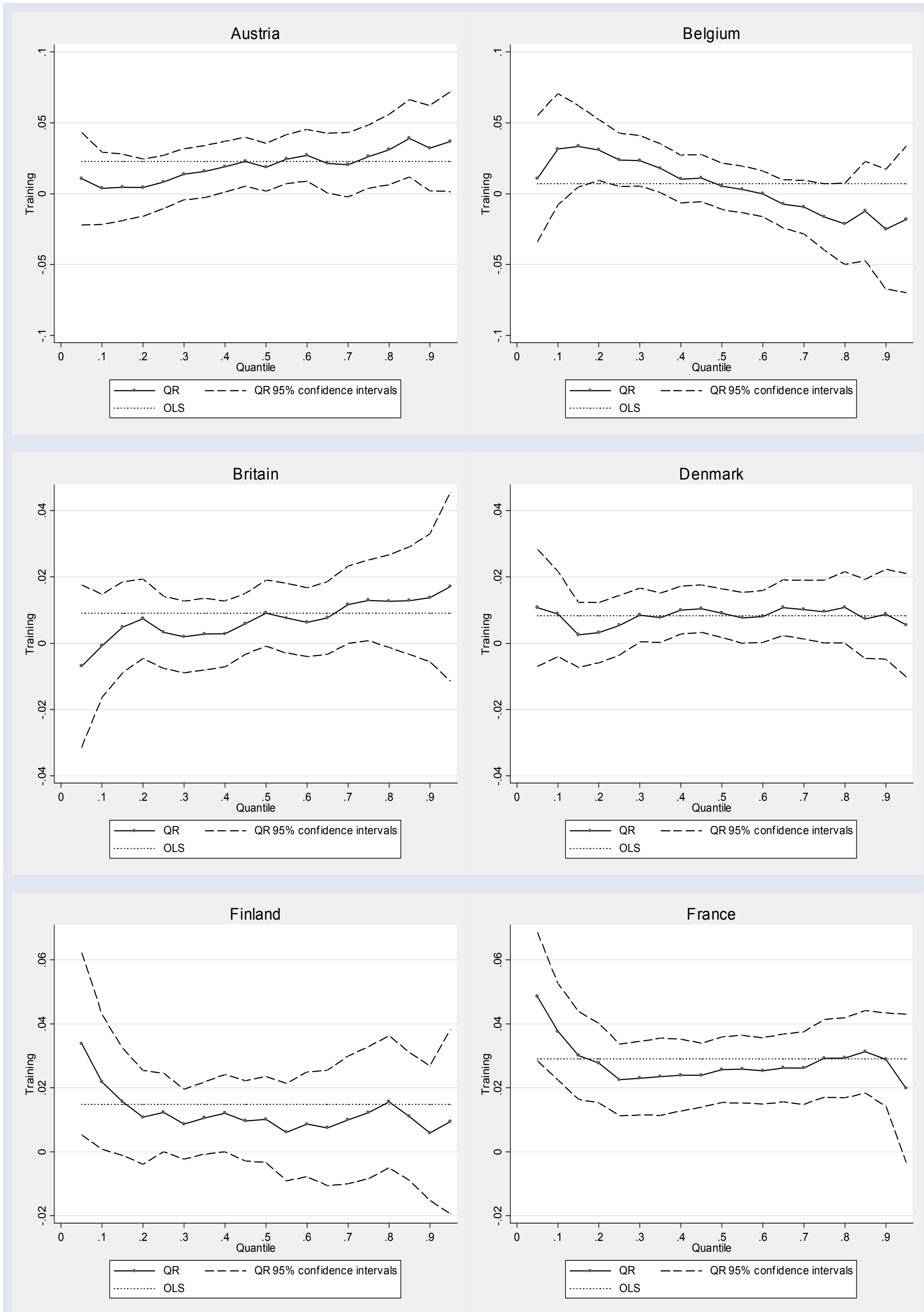
Figure 1: Private sector training



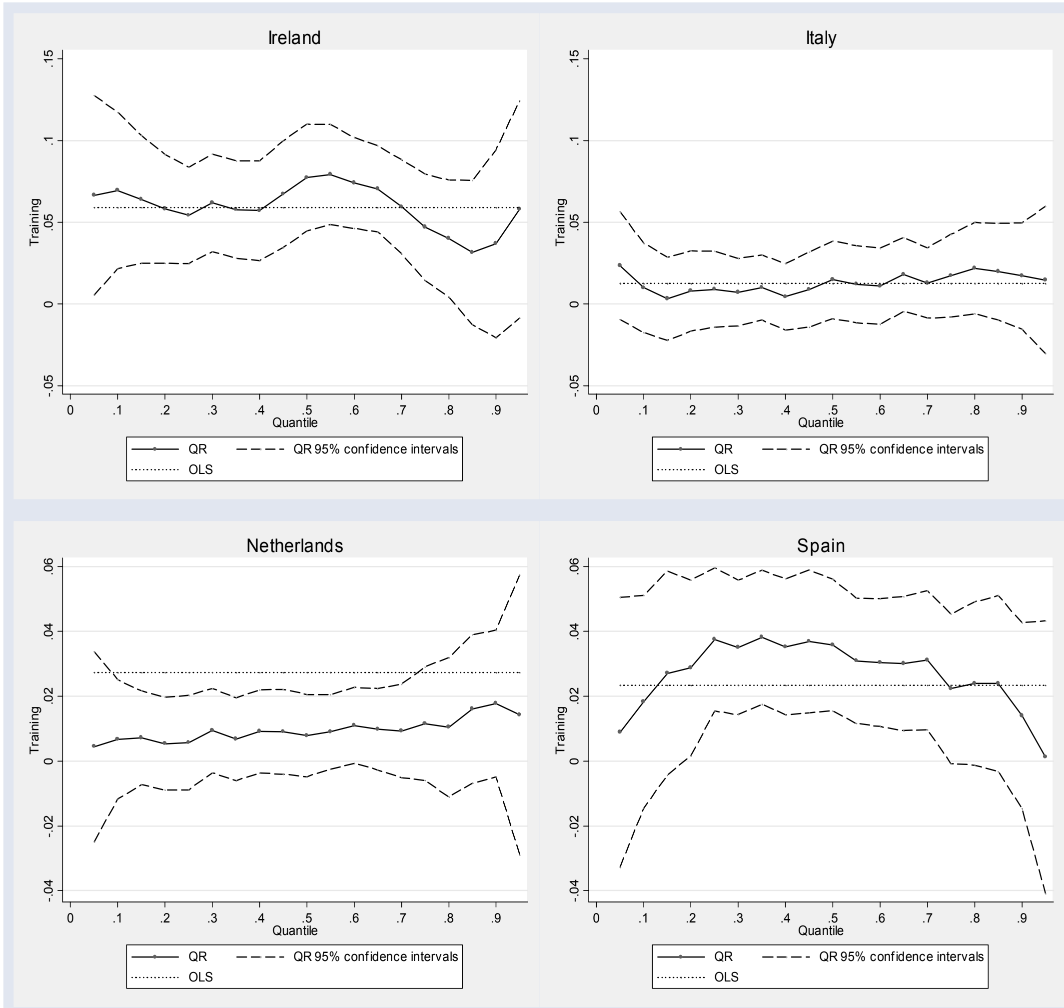

Ireland
Italy
Netherlands
Spain
Training
Quantile
QR
QR 95% confidence intervals
OLS

Table 1: Log hourly wage distributions in purchasing power parity (PPP) units

	Mean [1]	St dev [2]	Median [3]	10th percentile [4]	90th percentile [5]	90-10 differential [6]
Austria	2.330	0.384	2.301	1.929	2.807	0.878
Belgium	2.468	0.349	2.434	2.072	2.927	0.854
Britain	2.432	0.463	2.425	1.863	3.014	1.151
Denmark	2.689	0.311	2.651	2.336	3.123	0.786
Finland	2.326	0.395	2.279	1.905	2.838	0.933
France	2.201	0.458	2.157	1.696	2.789	1.093
Ireland	2.357	0.522	2.356	1.792	2.973	1.181
Italy	2.190	0.338	2.154	1.834	2.609	0.775
Netherlands	2.700	0.406	2.667	2.330	3.142	0.812
Spain	2.132	0.510	2.068	1.554	2.805	1.251

Notes: The log wage was calculated from the ECHP variables as log (wage) = log (PI211MG * (12/52) / PE005A) = log (normal gross monthly earnings from main job including overtime * (12/52) / hours in main job including overtime). It was then deflated to 1999 prices using harmonised indices of consumer prices (HICP) from the Eurostat Yearbook 2002, and converted to purchasing power parity (PPP) units using the ECHP variable PPPxx (where xx is the year).

Table 2: Training Participation across Europe for Private Sector Men in Employment Aged 25-54 Years

	Number of men observed [1]	Mean number of observed waves [2]	Annual training incidence (completed) [3]	Mean accumulated training count [4]
Austria	804	3.00	0.15	0.45
Belgium	603	3.00	0.10	0.31
Britain	1001	3.40	0.38	1.31
Denmark	715	3.44	0.38	1.31
Finland	788	2.37	0.32	0.77
France	1557	3.42	0.13	0.49
Ireland	598	3.23	0.05	0.17
Italy	1306	3.44	0.05	0.16
Netherlands	1288	3.90	0.06	0.24
Spain	1324	3.31	0.08	0.25

Note: column [3] reports the average proportion of men who have completed a training course since the previous interview; column [4] indicates the mean number of courses completed over the panel (which equals the product of columns [2] and [3]).

Table 3 – Estimated Returns to Training

	OLS	10%	25%	50%	75%	90%
Austria	0.0228*** (2.97)	0.0038 (0.29)	0.0084 (0.87)	0.0187** (2.16)	0.0262** (2.30)	0.0321** (2.09)
Belgium	0.0072 (0.80)	0.0315 (1.57)	0.0238** (2.49)	0.0053 (0.64)	-0.0163 (1.37)	-0.0250 (1.16)
Britain	0.0090* (1.77)	-0.0008 (0.10)	0.0033 (0.59)	0.0091* (1.79)	0.0130** (2.08)	0.0137 (1.39)
Denmark	0.0083** (2.30)	0.0088 (1.34)	0.0054 (1.17)	0.0091** (2.44)	0.0095** (1.97)	0.0087 (1.26)
Finland	0.0148** (2.11)	0.0219** (2.04)	0.0123** (1.97)	0.0102 (1.48)	0.0123 (1.16)	0.0059 (0.55)
France	0.0292*** (5.48)	0.0376*** (4.88)	0.0225*** (3.92)	0.0256*** (4.91)	0.0293*** (4.73)	0.0289*** (3.88)
Ireland	0.0589*** (3.96)	0.0695*** (2.85)	0.0542*** (3.62)	0.0773*** (4.64)	0.0470*** (2.83)	0.0369 (1.26)
Italy	0.0126 (1.56)	0.0099 (0.71)	0.0090 (0.76)	0.0148 (1.22)	0.0173 (1.34)	0.0172 (1.03)
Netherlands	0.0273*** (2.63)	0.0067 (0.71)	0.0057 (0.76)	0.0078 (1.21)	0.0115 (1.29)	0.0177 (1.54)
Spain	0.0233*** (2.79)	0.0183 (1.09)	0.0375*** (3.32)	0.0358*** (3.45)	0.0223* (1.90)	0.0140 (0.95)

Notes: (i) The model includes the wage in the first wave, dummies for whether training is still in progress, age, education, tenure, marital status, health status, any experience of unemployment since 1989, presence of children under 12, part-time status, fixed term and casual contracts, firm size, occupation, region (where possible), industry and year. Dummies were also included for cases where there were a very large number of missing values. (ii) Asterisks denote level of significance: * 10%, ** 5%, *** 1%.

Table 4 – F tests of Equality of Returns to Training

	θ = 0.25	θ = 0.50	θ = 0.75	θ = 0.90	Test of joint equality of all coefficients on the training variable
Austria					F(4,2366)=0.82
θ = 0.10	0.17	1.50	2.16	2.11	
θ = 0.25		1.59	2.08	1.96	
θ = 0.50			0.60	0.74	
θ = 0.75				0.18	
Belgium					F(4, 1760) = 2.78**
θ = 0.10	0.22	1.90	4.91**	4.11**	
θ = 0.25		4.93**	10.13***	5.09**	
θ = 0.50			4.08**	2.14	
θ = 0.75				0.21	
Britain					F(4, 3351) = 0.70
θ = 0.10	0.41	1.65	2.25	1.44	
θ = 0.25		1.58	1.90	0.95	
θ = 0.50			0.45	0.22	
θ = 0.75				0.01	
Denmark					F(4, 2414) = 0.26
θ = 0.10	0.36	0.00	0.01	0.00	
θ = 0.25		0.75	0.53	0.17	
θ = 0.50			0.01	0.00	
θ = 0.75				0.02	
Finland					F(4,1821) = 0.39
θ = 0.10	1.00	1.12	0.49	1.12	
θ = 0.25		0.11	0.00	0.28	
θ = 0.50			0.06	0.14	
θ = 0.75				0.33	
France					F(4, 5267) = 1.22
θ = 0.10	4.61**	2.22	0.92	0.74	
θ = 0.25		0.36	0.95	0.56	
θ = 0.50			0.43	0.18	
θ = 0.75				0.00	
Ireland					F(4, 1885) = 1.19
θ = 0.10	0.46	0.08	0.66	0.72	
θ = 0.25		1.76	0.13	0.30	
θ = 0.50			3.40*	1.80	
θ = 0.75				0.15	
Italy					F(4, 4433) = 0.10
θ = 0.10	0.01	0.11	0.21	0.14	
θ = 0.25		0.26	0.37	0.20	
θ = 0.50			0.05	0.02	
θ = 0.75				0.00	
Netherlands					F(4, 4971) = 0.23
θ = 0.10	0.01	0.01	0.15	0.53	
θ = 0.25		0.10	0.37	0.88	
θ = 0.50			0.26	0.74	
θ = 0.75				0.36	
Spain					F(4, 4332) = 1.07
θ = 0.10	1.70	1.04	0.05	0.04	
θ = 0.25		0.03	1.40	1.84	
θ = 0.50			1.77	1.91	
θ = 0.75				0.41	

Notes: Asterisks denote level of significance: * 10%, ** 5%, *** 1%.

Table 5 – Estimated Returns to Education

		OLS	10%	25%	50%	75%	90%
Austria	2nd level	0.0182 (1.17)	-0.0277 (1.05)	0.0305** (1.99)	0.0454*** (2.68)	0.0502*** (2.79)	0.0144 (0.52)
	3rd level	0.0668** (2.41)	0.0628 (1.36)	0.0567* (1.81)	0.0571 (1.53)	0.1274*** (2.78)	0.1171* (1.71)
Belgium	2nd level	0.0113 (0.96)	-0.0182 (0.95)	0.0013 (0.09)	0.0147 (1.15)	0.0052 (0.32)	0.0259 (1.04)
	3rd level	0.0754*** (4.95)	0.0497** (2.09)	0.0475*** (2.67)	0.0589*** (3.68)	0.0713*** (3.72)	0.1098*** (3.68)
Britain	2nd level	-0.0303** (2.09)	-0.0138 (0.70)	-0.0103 (0.68)	-0.0246** (1.97)	-0.0304* (1.92)	-0.0434* (1.83)
	3rd level	0.0046 (0.38)	-0.0001 (0.01)	0.0111 (0.74)	-0.0056 (0.54)	0.0028 (0.20)	0.0079 (0.33)
Denmark	2nd level	0.0243** (2.27)	-0.0181 (1.07)	0.0142 (1.34)	0.0127 (1.11)	0.0303** (2.19)	0.0704*** (2.79)
	3rd level	0.0594*** (4.49)	0.0083 (0.39)	0.0415*** (2.95)	0.0355** (2.38)	0.0718*** (3.65)	0.1446*** (4.73)
Finland	2nd level	0.0347** (2.45)	0.0771*** (2.94)	0.0386** (2.38)	0.0138 (0.97)	0.0074 (0.42)	0.0091 (0.39)
	3rd level	0.0592*** (3.21)	0.0824** (2.35)	0.0655*** (3.24)	0.0465** (2.44)	0.0290 (1.26)	0.0386 (1.12)
France	2nd level	0.0504*** (5.47)	0.0588*** (3.75)	0.0487*** (5.31)	0.0314*** (4.04)	0.0351*** (4.21)	0.0659*** (4.72)
	3rd level	0.1524*** (11.86)	0.1795*** (7.66)	0.1352*** (10.29)	0.0865*** (6.68)	0.1116*** (7.48)	0.1563*** (6.95)
Ireland	2nd level	0.0359** (2.37)	0.0278 (1.07)	0.0142 (0.85)	0.0302* (1.78)	0.0478** (2.14)	0.0511* (1.86)
	3rd level	0.1277*** (5.35)	0.1106** (2.45)	0.1158*** (4.88)	0.1138*** (4.33)	0.1293*** (3.24)	0.1947*** (3.63)
Italy	2nd level	0.0111 (1.45)	0.0365*** (2.65)	0.0305*** (3.37)	0.0197** (2.43)	0.0142 (1.32)	0.0012 (0.09)
	3rd level	0.1074*** (6.56)	0.1563*** (5.12)	0.1502*** (7.44)	0.1014*** (4.33)	0.0815*** (3.60)	0.1010*** (2.62)
Netherlands	2nd level	0.0280** (2.03)	0.0034 (0.22)	-0.0015 (0.18)	-0.0001 (0.02)	0.0123 (1.41)	0.0336*** (2.76)
	3rd level	0.1663*** (9.09)	0.0956*** (4.16)	0.0522*** (4.44)	0.0494*** (4.39)	0.0863*** (6.10)	0.1135*** (6.11)
Spain	2nd level	0.0452*** (4.01)	0.0633*** (3.25)	0.0364** (2.45)	0.0371*** (2.73)	0.0452*** (3.22)	0.0354* (1.75)
	3rd level	0.0876*** (6.68)	0.0861*** (4.16)	0.0756*** (4.66)	0.0692*** (4.91)	0.0855*** (5.20)	0.1048*** (4.88)

Notes: (i) The model includes the wage in the first wave, accumulated training, dummies for whether training is still in progress, age, tenure, marital status, health status, any experience of unemployment since 1989, presence of children under 12, part-time status, fixed term and casual contracts, firm size, occupation, region (where possible), industry and year. Dummies were also included for cases where there were a very large number of missing values. (ii) Asterisks denote level of significance: * 10%, ** 5%, *** 1%.

DATA APPENDIX: Selection of estimating samples

Unless otherwise stated, we applied the initial selection described in Section 3 of the text. We then dropped observations with missing or invalid data on the variables in the wage equations, that is principally: training, fixed term or casual contract, occupation, industry, region, establishment size, tenure, part-time status, education, health status, marital status and presence of children. Where the number of missing values was substantial, we also included a dummy variable for missing value observations in order to preserve the sample sizes. Finally, we kept only continuous sequences of observations from the first wave (usually ECHP wave 1) to ensure a complete record of training for each individual. The table details the number of observations remaining at each of these selection stages.

Country	Initial no. of obs after first selection	No. of obs with valid data	Additional selections used	Included missing value dummies	Included waves	No. of obs [ind] after selection of continuing spells	Other comments
Austria	3189	3029			3-6	2413 [804]	.
Belgium	3406	2680		Size	2-6	1809 [603]	.
Britain	5569	4246	Wave 6 deleted.	Industry, Fixed Term/Casual contract	2-5	3407 [1001]	No selection on training intensity missing for approx. half training events. Intensity not used. Training not dated.
Denmark	3249	3126		Industry	2-6	2461 [715]	
Finland	2386	2282		Industry, Occupation	4-6	1871 [788]	
France	7483	6589		Fixed Term/ Casual, Size, Occupation ,Industry	2-6	5322 [1557]	Training is not dated.
Ireland	2729	2643		Region	2-6	1932 [598]	
Italy	6944	6173			2-6	4489 [1306]	
Netherlands	7038	6719		Industry	2-6	5017 [1288]	No training finish dates or intensity available.
Spain	6445	6296		Region	2-6	4384 [1324]	