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MEASURING THE IMPACT OF ON THE JOB TRAINING ON JOB MOBILITY*

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This paper studies the effect of employer-provided training on the probability of subsequent job exit. Empirical evidence usually shows that the probability of receiving training by the employer is higher among those employees with the lowest expected rates of turnover. Therefore, it seems that firms provide training selectively. In this paper, we address the empirical question of to what extent this endogeneity problem leads to a spurious correlation between training receipt and job mobility. Using Spanish Data from the European Community Household Panel, we provide estimates that ignore the selection bias and compare the results with the ones obtained when correcting for the possible nonrandom selection between trainees and non-trainees. Overall, our results show that there is a negative correlation between on the job training and job mobility, but only for fired workers, and not for voluntary movers. Nonetheless, once the endogeneity problem is accounted, the negative effect becomes statistically nonsignificant for all types of movers.

Key words: on the job training, turnover, job mobility.

JEL Classification: M53.

This paper studies the effect of employer-provided training on the probability of subsequent job exit. It is a widely held view that firms' provided training is crucial to improve long-term economic performance. Moreover, a significant amount of schooling takes place once the individual has entered in the labour market, so training is relevant both for employees and employers. Sieben (2007) summarizes some of the reasons that explain the importance of firm-provided training. She emphasizes that training makes workers perform better in their jobs [Bartel (1995)], helps to adequate the skills acquired during initial education to skills required at the job [De Grip *et al*. (1998)], is an instrument to prevent skills obsolescence [Bishop (1997)], and improves workers' employability by increasing their career opportunities both inside and outside the firm [Groot and Maasen van den Brink (2000)].

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One of the main concerns with regards to the investment in training by firms is that it can be under its optimal level. The argument commonly used to explain this under-investment is the so called "poaching problem", that is, the probability that employees leave the firm after receiving the training and, thus, firms loose the opportunity to recover their investment. According to this, standard human capital theory argues that firms will only bear the cost of firm-specific training and not of general training. Nonetheless, in practice, employers usually bear part of the costs of general training, which is consistent with recent training literature that assumes imperfectly competitive labour markets. In any case, the absence of data on key theoretical constructs of the theory –general training, specific training, or productivity growth– implies that the only predictions of the theory that can be accurately tested relate to the effects of formal training on variables like wages or turnover. In this paper we focus on job mobility and our purpose is to address the empirical question whether those employees who receive training in their firm paid by the employer are more prone to quit, rather than testing different theories.

To address this question it is important to note that firms typically provide training to their employees selectively. This can be due to the above mentioned risk of losing the returns of training or because employers are better at assessing the ability of workers than the econometrician and provide training to those workers who are highly able. This implies that participation in training is not distributed at random. Furthermore, there might be factors unobserved by the econometrician –like aspirations, motivations and ambitions– that influence both training participation and job mobility behavior. This is the so called "selection bias problem", which implies that those workers who receive training would behave differently from those who do not, independently of any true causal effect of training on job mobility. In short, it is very likely that the probability of training receipt and the probability of subsequent job exit are not independent one to another. This endogeneity may lead to a spurious correlation between both variables.

Most of the empirical research on the effect of employer-provided training on subsequent job mobility have adopted a sequential approach in which typically the question to answer is the following: if an individual receives training in period t, how does his probability to move from his job in period t+1 vary? A consistent finding of the empirical models which do not account for the previous endogeneity problem is that training has a negative effect on job mobility. However, this result only has a causal interpretation if it is assumed that there are not unobserved determinants of mobility that also determine previous training participation. As emphasized before, this is difficult to maintain.

In this paper we present estimates that show the importance of accounting for the selection problem, pointing out that lack of control of endogeneity could lead to misleading policy recommendations. Using Spanish data from the European Community Household Panel (ECHP), we focus on the effect of what the ECHP calls "vocational training", because only in this case we have information on whether or not the training has been paid by the employer. We present separate estimates for workers who leave the firm voluntarily and fired workers in order to account for the potential observed and unobserved differences between these two groups of "movers".

To quantify the causal effect of training receipt on job mobility we treat these two variables as discrete. However, as opposed to the case of continuous variable models, instrumental variable methods are inappropriate for analyzing the relationship between two endogenous discrete variables [see Manski *et al.* (1992)]. Given this, we our preferred estimates are based on a switching probit model with endogenous switching. Although there are also nonparametric alternatives to estimate these types of models [see Manski (1990)], prior information assumptions are necessary if one is to do more than bound the probabilities. For that reason, our identification strategy is based on assumptions about the probability distribution of the endogenous variables, and also on exclusion restrictions that will help to identify the parameters of the model. Specifically, we use lagged values of the training variables as predetermined instruments and also information on whether or not the individual speaks a second language as an external instrument.

Our results show when the endogeneity problem is not accounted for that there is a negative effect of employer-paid training on job mobility, although this effect is only statistically significant for fired workers, and not for voluntary movers. However, once we account for the possible self-selection of the trainees, the negative effect of training on job mobility becomes statistically non-significant in all cases. Therefore, we do not find evidence that the training itself reduces the likelihood of leaving the job. There are other unobserved characteristics potentially correlated with training participation that need to be taken into account in order to have useful estimates of the effect of training on job mobility.

The organization of the paper is as follows. Section 1 reviews the related literature; Section 2 presents the econometric model and the identification strategy; Section 3 describes the data set used; Section 4 contains the estimation results; and, Section 5 concludes.

1. Empirical research on the effect of training on job mobility

There are a number of theories as to why workers change jobs. Many studies on training and job mobility take the Human Capital Theory [Becker (1964)] as a starting point. According to this theory, it is crucial the distinction between general and firm-specific training. Specific training increases an individual's productivity only at the firm in which the individual is employed, while general training also increases his productivity in other firms. In this setting employees alone pay for the costs of general training, while costs of firm-specific training are shared by both the worker and the firm. In this model investment on training is on its optimal level and specific training should unambiguously be associated with lower turnover rates while it is not expected any effect of general training on the employees' inclination to quit.

This theory, however, is based on the assumption that labour market is perfectly competitive. Alternative theoretical models relax this assumption. According to these models employers would be willing to bear part of the costs for general training. This is the case, for example, of Stevens (1994), Katz and Ziderman (1990) or Acemoglu and Pischke (1998). The first one assumes imperfect competition in the labour market while the others assume informational asymmetries. In these more realistic frameworks deviations from the optimal level of training are possible and both general and specific training could be related to job mobility.

From an empirical point of view, several papers have tried to analyze the relationship between general or specific training and job mobility. Using data from call centre agents in the Netherlands, Sieben and De Grip (2004) estimate logistic models and obtain that only firm-specific training decreases inclination to quit for another job inside the sector. Green *et al*. (2000), by the estimation of ordered probit models, show that firm-specific training has a negative impact on job mobility in Britain, while general training has a non-significant impact.

It must be noted, however, that many available data sets do not distinguish between general and specific training. Moreover, in practice most of the training is a blend of specific and general training. For this reason many empirical studies focus on who pay for or/and organize the training offered to the employees. Some examples are Parent (2003), Zweimüller and Winter-Ebmer (2003), Elias (1994) and Lynch (1991).

Using Canadian data, Parent (2003) estimates a Cox proportional hazard model and finds a negative relation between the receipt of employer supported training and the breakdown of the labour relation. Zweimüller and Winter-Ebmer (2003), using data from Switzerland, distinguish between "employer-provided" and "self-financed" training. The first one is associated with firm-specific training and the second one is associated with general training. By the estimation of probit models they find that firm-specific training induces lower mobility for women, while there is no significant impact of general training. For Great Britain, Elias (1994) estimates logit models for the probability of a job completion. The results point to a negative effect of training on female labour mobility, while for males the effect is barely significant. In turn, Lynch (1991) focuses on the determinants of leaving an employer among young workers in their first years of work in the United States. By the estimation of Cox proportional hazard models, the results show that those workers who had some formal "on-the-job training" were less likely to leave their employer, while those who participated in some form of "off-the-job training" were more likely to leave.

One of the major drawbacks of some of the existing literature is that training is treated as an exogenous determinant of job mobility and the reverse-causation problem is not controlled for. As pointed out by Card and Sullivan (1988), the measurement of training effects in the absence of random assignment into trainees and non-trainees groups is extremely difficult. Some studies address this issue within a duration model framework and account for unobserved effects correlated with training and mobility by modelling individual-specific baseline hazards [see, for instance, Korpi and Mertens (2003), Parent (2003) or Elias (1994)]. Some other authors, like Veum (1997), account for the endogeneity problem using as instruments for training variables related to institutional characteristics of the individual's locality trying to reflect the individual's potential access to training. By the estimation of Cox proportional hazard models, he provides only limited evidence that training reduces turnover. Nonetheless, the instruments used for identification in Veum's paper are only moderately successful in predicting training receipt. Within a different framework, Sieben (2007) studies the effect of training on search behavior by estimating logit models. She controls for selectivity by applying Heckman two-steep methods using as exclusion restrictions variables related to the previous educational level of the individual. Her results show that there is no significant self-selection for men, while for women she did not find any variable which affects training and not search behavior. Another possibility is to rule out the unobserved effects using a first-differences approach [see Greenhalgh and Stewart (1987)]. Nonetheless, this approach has greater potential to further enhance any measurement errors present in the data and moreover, it is not straightforward to apply in non-linear models.

In this paper we use an identification strategy based on the estimation of a switching probit model with endogenous switching. As there is no obvious identifying restriction that could be used to perform over-identification tests, we use the non-linearity of the model as the minimum identifying assumption. Nevertheless, identification based solely on arbitrary functional form assumptions is fragile. In this sense, the presence of a regressor in the training equation that does not directly affect the mobility decision could improve identification of the parameters of the model[1]. Altonji and Shakotko (1987), in the context of the effect of tenure on wages, propose using the variation of tenure over a job match as instrumental variable for tenure. Parent (1999) extends this methodology to the study of the effect of training on wages. However, given the discrete nature of our endogenous variables, this approach is not valid for us, since there is no enough variation in that instrument to explain the training variable. We have, therefore, relied on a distributional assumption element using in addition some exclusion restrictions to identify the parameters of the model. Specifically, we try to capture certain aspects of the ability of the worker that could influence on the training probability using information on whether or not the individual speaks a second language. Moreover, we take advantage of the panel structure of the data and use also two lagged values of the training variables as predetermined instruments.

2. The econometric model

The empirical question of interest is whether training causally affects job mobility. To measure this effect it is useful to define two hypothetical mobility outcomes, M_0 and M_1. Each worker, i, is characterized by values of the variables (M_{i1}, M_{i0}, T_i, x_i). Variable M_{i1} indicates the outcome if the individual were to take the training course: $M_{i1} = 0$ if the individual does not move and $M_{i1} = 1$ otherwise. Similarly, M_{i0} indicates the outcome if the individual were not to participate in the training program. Here x is a vector of individual and job characteristics. The binary variable T indicates training participation in the previous period and is defined as $T_i = 1$ if the individual participates and $T_i = 0$ otherwise.

We can measure the effect of training on job mobility for a particular individual by the difference $\Pr(M_{i1} = 1|x_i)$-$\Pr(M_{i0} = 1|x_i)$. It measures how a particular individual would change job mobility behavior if his training behavior switched from $T_i = 0$ to $T_i = 1$. However, for each individual we only observe the value of M_{i1} or M_{i0}, and the other value is censored. As pointed out by Manski *et al.* (1992), the sampling process generating the data only identifies the conditional probabilities $\Pr(M_{i1} = 1|x_i, T_i = 1)$ and $\Pr(M_{i0} = 1|x_i, T_i = 0)$. Therefore, in the absence of prior information, the data cannot identify the parameters of interest, $\Pr(M_{i1} = 1|x_i)$ and $\Pr(M_{i0} = 1|x_i)$.

(1) As Dearden *et al.* (1996) recognize it is difficult to suggest variables which are correlated with training but not with mobility. Thus, in practice, identification would be through functional form assumptions.

One solution to this identification problem, typically used in linear models, is to use the standard two-stage or instrumental variables method. Nevertheless, the presence of a dummy endogenous regressor in a binary choice model makes the analysis differ substantially from that in continuous variable models. More precisely, the standard two-stage method leads to an inconsistency with the statistical assumptions of the nonlinear discrete models. Moreover, the alternative linear probability model is incompatible with the observed data when dummy endogenous regressors are present in a binary choice model [see Carrasco (2001) for a detailed discussion on this issue].

Given this problem, the identification of the effect of training on job mobility depends crucially on the available prior information to the econometrician. As in Carrasco (2001), that prior information about the joint probability distribution of (M_{i1}, M_{i0}, T_i) is expressed through the formulation of a trivariate probit model.

Let us then consider the following switching probit model for N individuals:

$$M_i = \begin{cases} M_{i1} = \Gamma\left(\alpha_1 x_i + u_{i1} \geq 0\right), & T_i = 1; \\ M_{i0} = \Gamma\left(\alpha_0 x_i + u_{i0} \geq 0\right), & T_i = 0; \end{cases} \qquad [1]$$

and

$$T_i = \Gamma\left(\beta q_i + \varepsilon_i \geq 0\right), \qquad (i = 1,...,N), \qquad [2]$$

where Γ is the indicator function, α_1, α_0 and β are vectors of coefficients which include a constant term, M_i is the observed job mobility outcome for individual i, and q is a vector of variables which can include an exclusion restriction. We assume that (u_{i1}, u_{i0}, ε_1) are jointly normally distributed with zero mean vector and covariance matrix.

$$\sum = \begin{pmatrix} 1 & \rho_{10} & \rho_{1\varepsilon} \\ & 1 & \rho_{0\varepsilon} \\ & & 1 \end{pmatrix} \qquad [3]$$

We estimate several models which differ in their assumptions about the covariance matrix of the disturbances. The most general one does not impose any restrictions on the covariance matrix (u_{i1}, u_{i0}, ε_1)[2]. This is a switching probit model with endogenous switching. This is our preferred model since training participation and job mobility outcomes may be jointly determined by processes that cannot be directly observed. In the context of the latent-variable model previously presented, this means that the disturbances (u_{i1}, u_{i0}, ε_1) are statistically dependent. Notice that the standard bivariate probit arises as an especial case in which $\rho_{0\varepsilon} = \rho_{1\varepsilon}$.

As emphasized before, within this framework, the main problem we face is given by the fact that the data are not able to identify $\Pr(M_1 = 1|x)$ and $\Pr(M_0 = 1|x)$. Given that the two variables of interest, mobility and training, are discrete, one can not apply the standard two stage IV approach as in continuous variable models. The

(2) This model is similar to the one estimated by Manski *et al*. (1992) in the context of the effect of family structure during adolescence on high school graduation.

reason is that since training is a binary indicator its distribution cannot be normal, and as a consequence, two-stage or instrumental-variable methods are not valid alternatives for estimating this type of nonlinear models. Hence, as it is pointed out by Manski *et al*. (1992), the possibilities for inference depend critically on the assumptions about the distribution of the disturbances of the model, as well as on the available prior information about the process generating the outcomes of interest. In this paper, we assume that the disturbances are distributed trivariate normal and also use some exclusion restrictions to improve the identification of the causal effect of interest. In particular, we use an "external" instrument given by an indicator of whether or not the individual speaks a second language. We also use as instruments lagged values of the training variable. Notice that by using predetermined instruments we account for the potential persistence in the training variable. The identifying assumption behind is that, once we account for current training, there is no a direct effect on mobility between t and t+1 of having received training in t-1 and before. The only effect of training in t-1 and before is through its effect on training in t[3].

Dropping out the individual subscripts, the log-likelihood function of the model, from which maximum likelihood estimates can be obtained, is as follows:

$$L(\alpha_0,\alpha_1,\beta,\rho_{0\varepsilon},\rho_{1\varepsilon}) = \sum_{M=0,T=0} \log P_{00} + \sum_{M=0,T=1} \log P_{01} + \sum_{M=1,T=0} \log P_{10} + \sum_{M=1,T=1} \log P_{11}, \qquad [4]$$

where

$$\begin{aligned} P_{00} &= \Pr(M=0,T=0) = \Phi(-\alpha_0 x, -\beta q; \rho_{0\varepsilon}), \\ P_{01} &= \Pr(M=0,T=1) = \Phi(-\alpha_1 x) - \Phi(-\alpha_1 x, -\beta q; \rho_{1\varepsilon}), \\ P_{10} &= \Pr(M=1,T=0) = \Phi(-\beta q) - P_{00}, \\ P_{11} &= \Pr(M=1,T=1) = \Phi(-\beta q) - P_{10} = 1 - P_{00} - P_{01} - P_{10}. \end{aligned} \qquad [5]$$

Notice that the model which assumes that ε is statistically independent of (u_1, u_0), imposes that training is exogenous to job mobility (that is to say, $\rho_{1\varepsilon} = 0$ and $\rho_{0\varepsilon} = 0$). This assumption would mean that the unobserved factors that affect job mobility and training are uncorrelated. In that case, the sampling process would be able to identify the probability of interest, $\Pr(M = 1 | x_i, T_i)$, and the parameters can be estimated by maximizing the binary probit likelihood. This model is estimated as a benchmark.

3. Data description

The data come from the last two waves of the European Community Household Panel (ECHP) corresponding to years 2000 and 2001 for Spain[4]. This is a longitudinal data set which allows us to measure the effect of training in one period on labour

(3) This assumption is standard in the panel data literature.

(4) This data set has been also used, for instance, by Arulampalam *et al*. (2010) to study the effect of training for workers at different quantiles of the wage distribution in ten European Union countries.

market status in subsequent periods[5]. Every year the selected households are interviewed about issues relating to demographics and labour market behavior.

Our sample comprises individuals employed in the first wave. Specifically, we select those employees who declare that are normally working 15 or more hours per week in 2000. We focus on this group because some important variables for the analysis, as tenure or firm size, are only available for individuals working 15 hours or more. We eliminate those in self-employment and those working with an employer in paid apprenticeship. We also exclude employees in the agricultural sector and those over 60 years old (in order to mitigate the effect of job exit due to retirement). The final sample size is 2,707 observations.

The dependent variable is an indicator of job mobility. It takes the value 1 for those individuals that in the second wave are not in the same job held in the first one. This definition of the job mobility variable is adopted, for example, by Elias (1994) or Mincer and Jovanovic (1981), and implies that it takes value 1 also for individuals who move to unemployment or inactivity. It must be noted, however, that the most common movement is to another job (66.0% versus 13.4% who become unemployed and 20.6% who leave the labour market)[6]. On the other hand, in the case of the movements to another job, we have also used information on tenure in order to capture exits from the firm and not changes of job within the same firm, which are not relevant in this context. On the whole, 22.6% of the individuals change their labour situation between the two waves. We have also performed separate estimates that account for the reason why the workers leave the job. Specifically, we estimate a model in which the mobility variable takes the value 1 for movers who have been fired (these are 12.6% of the sample), and another model for those who have voluntarily left the firm, who represent 9.8% of the sample.

With respect to the training variable, the ECHP distinguishes between "general" and "vocational" courses. We focus on vocational training because only in this case we know if the training has been paid and/or organized by the employer[7]. We define training to take the value 1 if the individual has received such training since January in the previous year, and 0 otherwise. About 10.3% of individuals in the total sample have received vocational training paid or organized by their employer[8], while this figure is 11.2% and 11.7% for the subsamples used to estimate the models for fired workers and voluntary movers, respectively.

(5) We restrict the analysis to the last two waves of the survey because the focus of our research is to analyze endogeneity issues, and we want to keep a homogeneous sample without the potential influence of business cycle effects.

(6) We have also considered a different measure of job mobility which excludes those individuals who move to unemployment or inactivity. The results, available upon request, do not change.

(7) The type of information on general training available in this data set does not allow us to analyze the effect of this type of training. The definition of "general training" in this survey is just referred to secondary and university education, and this is not the type of general training that it would be of interest for us. We focus on the training received on the job and paid by the employer because we are interested on the problem faced by the employers if they lose the returns to the investment on certain workers.

(8) The distribution of the type of vocational training, according to the information in the survey, is the following: (i) specific vocational training at a vocational school (24.6% of the total sample), (ii) specific vocational training within a system providing both work experience and a complementary instruction elsewhere (6.8%), (iii) specific vocational training in a working environment (60.7%), and (iv) other (7.9%).

The explanatory variables used in the estimation refer to socio-demographic variables related to the individual and to variables related to the job and the firm in which the individual was employed in the first wave[9]. With respect to socio-demographic characteristics we include dummy variables for gender, marital status, and for the presence of children under the age of 12. We also take into account the age (4 dummies) and the educational level (3 dummies) of the individual according to the International Standard Classification of Education. The characteristics of the job held in the first wave are included in terms of the type of contract (temporary or not), part-time or full-time employment, and tenure. We also account for the job status using three dummies variables indicating if the job held by the employee is (i) supervisory; (ii) intermediate; or (iii) non-supervisory. Firm's characteristics, such us private or public sector and service sector are also included. We capture the size of the firm through three dummy variables which take the value 1 for small (less than 100 employess), medium (between 100 and 500 employess), and large firms (with more thant 500 employess), respectively[10].

The sample characteristics are presented in Tables 1, 2, and 3. Table 1 offers descriptive information for what we called "total sample", which is used for the estimations in which the mobility variable does not distinguish between fired workers and voluntary movers. Tables 2 and 3 correspond to the samples used to estimate the models for fired workers and for voluntary movers, respectively[11]. Means are calculated for the whole sample and by sub-samples of trained and non-trained and workers who have changed their labour situation and those who haven't.

We observe that job change is more frequent among those that have not received training and that the percentage of trained is higher among those who have not change their labour situation. This points to a negative relationship between employer-provided training and subsequent job exit, for the three samples considered. If we compare trained and non-trained sub-samples we can see that in the first group there are relatively more women. Also, this group of individuals are relatively older, more educated and with more tenure in their current job. On the contrary, in the non-trained sub-sample there are relatively more temporary workers. With respect to the job status, this is higher among the trained group as well as the percentage of public and service sector and large firm employees. Comparing the employees who change their labour situation with those who haven't changed it we see that "movers" are relatively younger, less educated and with less tenure. They are more often temporary workers and held lower positions in their firms which, also, tend to be smaller. Finally, they are to a lesser extent employees in the public or service sectors.

(9) Other variables, like the quality of the training programs, could also be relevant to explain the effect of training on job exit. Unfortunately, in our data set we do not have this information.

(10) Notice that there could be other unobservable variables of the firm potentially correlated with the error term of the model. Nonetheless, given the characteristics of the data set, it is difficult to deal with them. One possibility could be to include firm's specific fixed effects, but this would require having data in which the cross sectional unit was the firm and not the individual.

(11) Notice that we do not use exactly the same individuals since for the last two samples we need information about the reason why the worker left the firm, which is missing for some individuals of the total sample and we have preferred to keep as many individuals as possible in the total sample. We have performed estimates usging exactly the same observations and the results do not change.

Table 1: SAMPLE MEANS. TOTAL SAMPLE

	TOTAL	$T = 1$	$T = 0$	$M = 1$	$M = 0$
Training	0.103 (0.30)	–	–	0.031 (0.17)	0.126 (0.33)
Mobility	0.226 (0.42)	0.068 (0.25)	0.244 (0.43)	–	–
Gender and family					
Women	0.366 (0.48)	0.414 (0.49)	0.361 (0.48)	0.396 (0.49)	0.358 (0.48)
Married	0.664 (0.47)	0.750 (0.43)	0.654 (0.48)	0.548 (0.50)	0.698 (0.46)
Children	0.339 (0.47)	0.389 (0.49)	0.333 (0.47)	0.318 (0.47)	0.345 (0.48)
Age					
16 – 25	0.113 (0.32)	0.028 (0.17)	0.123 (0.33)	0.229 (0.42)	0.079 (0.27)
26 – 35	0.331 (0.47)	0.293 (0.46)	0.335 (0.47)	0.393 (0.49)	0.313 (0.46)
36 – 45	0.295 (0.46)	0.404 (0.49)	0.282 (0.45)	0.198 (0.40)	0.323 (0.47)
46 – 60	0.261 (0.44)	0.275 (0.48)	0.260 (0.44)	0.180 (0.38)	0.285 (0.45)
Education					
Less than upper secondary	0.456 (0.50)	0.175 (0.38)	0.488 (0.50)	0.565 (0.50)	0.424 (0.49)
Upper secondary education	0.195 (0.40)	0.200 (0.40)	0.195 (0.40)	0.172 (0.38)	0.202 (0.40)
Tertiary education	0.349 (0.48)	0.625 (0.48)	0.317 (0.47)	0.263 (0.44)	0.374 (0.48)
Tenure					
Until 3 years	0.453 (0.50)	0.189 (0.39)	0.483 (0.50)	0.768 (0.42)	0.361 (0.48)
4 – 6 years	0.106 (0.31)	0.129 (0.34)	0.103 (0.30)	0.082 (0.27)	0.113 (0.32)
7 or more years	0.441 (0.50)	0.682 (0.47)	0.414 (0.49)	0.150 (0.36)	0.526 (0.50)
Contract					
Temporary	0.277 (0.45)	0.100 (0.30)	0.297 (0.46)	0.592 (0.49)	0.185 (0.39)
Part-time	0.048 (0.21)	0.014 (0.12)	0.052 (0.22)	0.072 (0.26)	0.042 (0.20)
Job status					
Supervisory	0.079 (0.27)	0.161 (0.37)	0.070 (0.25)	0.042 (0.20)	0.089 (0.29)
Intermediate	0.189 (0.39)	0.282 (0.45)	0.178 (0.38)	0.100 (0.30)	0.215 (0.41)
Non-supervisory	0.732 (0.44)	0.557 (0.50)	0.752 (0.43)	0.858 (0.35)	0.696 (0.46)
Sector					
Services	0.625 (0.48)	0.782 (0.41)	0.607 (0.49)	0.552 (0.50)	0.646 (0.48)
Public sector	0.248 (0.43)	0.421 (0.49)	0.228 (0.42)	0.175 (0.38)	0.270 (0.44)
Size					
Small	0.693 (0.46)	0.525 (0.50)	0.712 (0.45)	0.768 (0.42)	0.671 (0.47)
Medium	0.164 (0.37)	0.239 (0.43)	0.155 (0.36)	0.144 (0.35)	0.169 (0.38)
Large	0.143 (0.35)	0.236 (0.43)	0.133 (0.34)	0.088 (0.28)	0.160 (0.37)
Instruments					
Training t-1	0.102 (0.30)	0.350 (0.48)	0.073 (0.26)	0.054 (0.23)	0.115 (0.32)
Training t-2	0.118 (0.32)	0.325 (0.47)	0.094 (0.29)	0.049 (0.22)	0.138 (0.34)
Second language	0.148 (0.36)	0.306 (0.46)	0.130 (0.34)	0.139 (0.35)	0.151 (0.36)
Nº observations	2,707	280	2,427	611	2,096

Note: Standard deviations in parentheses.

Source: Our estimations using ECHP.

Table 2: Sample means. Fired workers

	TOTAL	$T = 1$	$T = 0$	$M = 1$	$M = 0$
Training	0.112 (0.31)	–	–	0.023 (0.15)	0.125 (0.33)
Mobility	0.126 (0.33)	0.026 (0.16)	0.138 (0.35)	–	–
Gender and family					
Women	0.365 (0.48)	0.414 (0.49)	0.359 (0.48)	0.417 (0.49)	0.358 (0.48)
Married	0.677 (0.47)	0.754 (0.43)	0.668 (0.47)	0.536 (0.50)	0.698 (0.46)
Children	0.342 (0.47)	0.396 (0.49)	0.336 (0.47)	0.328 (0.47)	0.345 (0.48)
Age					
16 – 25	0.097 (0.30)	0.026 (0.16)	0.106 (0.31)	0.222 (0.42)	0.079 (0.27)
26 – 35	0.324 (0.47)	0.287 (0.45)	0.328 (0.47)	0.397 (0.49)	0.313 (0.46)
36 – 45	0.306 (0.46)	0.414 (0.49)	0.293 (0.46)	0.192 (0.39)	0.323 (0.47)
46 – 60	0.273 (0.45)	0.273 (0.45)	0.273 (0.45)	0.189 (0.39)	0.285 (0.45)
Education					
Less than upper secondary	0.449 (0.50)	0.176 (0.38)	0.483 (0.50)	0.619 (0.49)	0.424 (0.49)
Upper secondary education	0.197 (0.40)	0.205 (0.40)	0.196 (0.40)	0.162 (0.37)	0.202 (0.40)
Tertiary education	0.354 (0.48)	0.619 (0.49)	0.321 (0.47)	0.219 (0.41)	0.374 (0.48)
Tenure					
Until 3 years	0.420 (0.49)	0.179 (0.38)	0.451 (0.50)	0.834 (0.37)	0.361 (0.48)
4 – 6 years	0.109 (0.31)	0.131 (0.34)	0.106 (0.31)	0.080 (0.27)	0.113 (0.32)
7 or more years	0.471 (0.50)	0.690 (0.46)	0.443 (0.50)	0.086 (0.28)	0.526 (0.50)
Contract					
Temporary	0.247 (0.43)	0.090 (0.29)	0.267 (0.44)	0.682 (0.47)	0.185 (0.39)
Part-time	0.043 (0.20)	0.011 (0.11)	0.047 (0.21)	0.056 (0.23)	0.042 (0.20)
Job status					
Supervisory	0.081 (0.27)	0.153 (0.36)	0.072 (0.26)	0.023 (0.15)	0.089 (0.29)
Intermediate	0.197 (0.40)	0.291 (0.46)	0.185 (0.39)	0.073 (0.26)	0.215 (0.41)
Non-supervisory	0.722 (0.45)	0.556 (0.50)	0.743 (0.44)	0.904 (0.30)	0.696 (0.46)
Sector					
Services	0.631 (0.48)	0.784 (0.41)	0.612 (0.49)	0.523 (0.50)	0.646 (0.48)
Public sector	0.259 (0.44)	0.422 (0.49)	0.238 (0.43)	0.182 (0.39)	0.270 (0.44)
Size					
Small	0.682 (0.47)	0.519 (0.50)	0.703 (0.46)	0.761 (0.43)	0.671 (0.47)
Medium	0.166 (0.37)	0.246 (0.43)	0.156 (0.36)	0.146 (0.35)	0.169 (0.38)
Large	0.152 (0.36)	0.235 (0.42)	0.141 (0.35)	0.093 (0.29)	0.160 (0.37)
Instruments					
Training t-1	0.106 (0.31)	0.358 (0.48)	0.074 (0.26)	0.040 (0.20)	0.115 (0.32)
Training t-2	0.126 (0.33)	0.328 (0.47)	0.100 (0.30)	0.043 (0.20)	0.138 (0.34)
Second language	0.147 (0.35)	0.291(0.46)	0.129 (0.33)	0.119 (0.32)	0.151 (0.36)
Nº observations	2,398	268	2,130	302	2,096

Note: Standard deviations in parentheses.

Source: Our estimations using ECHP.

Table 3: SAMPLE MEANS. VOLUNTARY EXITS

	TOTAL	$T = 1$	$T = 0$	$M = 1$	$M = 0$
Training	0.117 (0.32)	–	–	0.048 (0.21)	0.125 (0.33)
Mobility	0.098 (0.30)	0.040 (0.20)	0.106 (0.31)	–	–
Gender and family					
Women	0.358 (0.48)	0.408 (0.49)	0.352 (0.48)	0.364 (0.48)	0.358 (0.48)
Married	0.681 (0.47)	0.750 (0.43)	0.672 (0.47)	0.531 (0.50)	0.698 (0.46)
Children	0.340 (0.47)	0.386 (0.49)	0.333 (0.47)	0.289 (0.45)	0.345 (0.48)
Age					
16 – 25	0.096 (0.29)	0.026 (0.16)	0.105 (0.31)	0.250 (0.43)	0.079 (0.27)
26 – 35	0.321 (0.47)	0.279 (0.45)	0.327 (0.47)	0.399 (0.49)	0.313 (0.46)
36 – 45	0.310 (0.46)	0.412 (0.49)	0.297 (0.46)	0.193 (0.40)	0.323 (0.47)
46 – 60	0.273 (0.45)	0.283 (0.45)	0.271 (0.44)	0.158 (0.37)	0.285 (0.45)
Education					
Less than upper secondary	0.435 (0.50)	0.177 (0.38)	0.469 (0.50)	0.531 (0.50)	0.424 (0.49)
Upper secondary education	0.201 (0.40)	0.202 (0.40)	0.201 (0.40)	0.193 (0.40)	0.202 (0.40)
Tertiary education	0.364 (0.48)	0.621 (0.49)	0.330 (0.47)	0.276 (0.45)	0.374 (0.48)
Tenure					
Until 3 years	0.399 (0.49)	0.184 (0.39)	0.428 (0.49)	0.754 (0.43)	0.361 (0.48)
4 – 6 years	0.111 (0.31)	0.118 (0.32)	0.110 (0.31)	0.088 (0.28)	0.113 (0.32)
7 or more years	0.490 (0.50)	0.698 (0.46)	0.462 (0.50)	0.158 (0.37)	0.526 (0.50)
Contract					
Temporary	0.220 (0.41)	0.092 (0.29)	0.237 (0.43)	0.548 (0.50)	0.185 (0.39)
Part-time	0.045 (0.21)	0.015 (0.12)	0.049 (0.22)	0.075 (0.26)	0.042 (0.20)
Job status					
Supervisory	0.087 (0.28)	0.158 (0.37)	0.078 (0.27)	0.062 (0.24)	0.089 (0.29)
Intermediate	0.205 (0.40)	0.287 (0.45)	0.194 (0.40)	0.118 (0.32)	0.215 (0.41)
Non-supervisory	0.708 (0.45)	0.555 (0.50)	0.728 (0.45)	0.820 (0.38)	0.696 (0.46)
Sector					
Services	0.636 (0.48)	0.756 (0.42)	0.618 (0.49)	0.544 (0.50)	0.646 (0.48)
Public sector	0.256 (0.44)	0.415 (0.49)	0.235 (0.42)	0.136 (0.34)	0.270 (0.44)
Size					
Small	0.679 (0.47)	0.522 (0.50)	0.700 (0.46)	0.754 (0.43)	0.671 (0.47)
Medium	0.168 (0.37)	0.243 (0.43)	0.158 (0.37)	0.158 (0.37)	0.169 (0.38)
Large	0.153 (0.36)	0.235 (0.42)	0.142 (0.35)	0.088 (0.28)	0.160 (0.37)
Instruments					
Training t-1	0.110 (0.31)	0.357 (0.48)	0.078 (0.27)	0.057 (0.23)	0.115 (0.32)
Training t-2	0.128 (0.33)	0.324 (0.47)	0.102 (0.30)	0.035 (0.18)	0.138 (0.34)
Second language	0.151 (0.36)	0.301 (0.46)	0.132 (0.34)	0.158 (0.37)	0.151 (0.36)
Nº observations	2,324	272	2,052	228	2,096

Note: Standard deviations in parentheses.

Source: Our estimations using ECHP.

With respect to the instruments used, and in particular to the second language indicator, on the whole sample 14.8% of the individuals declare speaking a second language. As mentioned, we use this variable as an instrument in the estimation. Therefore, it should be desirable that it was correlated with the training but not with the mobility variable, once current training is taken into account. In this sense, if we compare the trained and non-trained sub-samples we can see that the percentage of individuals speaking a second language is higher among those who have received training (30.6% versus 13.0%). On the contrary, the percentage of individuals speaking a second language among employees who change their labour situation is quite similar to that for those who have not change it (13.9% versus 15.1%)[12]. As explained, with this instrument we try to capture certain aspects of the ability of the worker that could influence on the training probability. Finally, the sample means for the lagged values of the training variable, which complement the set of instruments, suggest a high persistence in this variable.

4. Estimation results

In this section we report the estimates from the different models previously described. We present and compare two sets of estimates: one from the model that treats training as strictly exogenous and another one from the model that accounts for the endogeneity of training participation. We perform both set of estimates for the total sample and for the sub-samples of fired workers and voluntary movers separately. For models in which endogeneity is accounted for, we cannot reject the null hypothesis $\rho_{1\varepsilon} = \rho_{0\varepsilon}$, therefore we only report estimates imposing this restriction. In principle we allow all the parameters in the equation for M_1 to differ from those in the equation for M_0 ($\alpha_1 \neq \alpha_0$). Nonetheless, we do not obtain significant differences among them, except for the constant term, which measures the effect of training. For that reason, we only present the results for which only the constant differs in both equations.

The qualitative impact of the variables is discussed in terms of the sign and statistical significance of the estimated coefficients. In order to assess the economic significance of the effects we also report predicted probabilities. Specifically, to evaluate the effect of training participation on the exit probability, we calculate the average effect for all individuals. For each individual we compute

$$\hat{M}_{i0} = E\left(M_{i0} \mid x_i\right) = \Phi\left(\hat{\alpha}_0 x_i\right), \quad i = 1, ..., N,$$

and [6]

$$\hat{M}_{i1} = E\left(M_{i1} \mid x_i\right) = \Phi\left(\hat{\alpha}_1 x_i\right), \quad i = 1, ..., N,$$

where N is the total number of individuals considered (the whole sample, or the sample for fired workers and voluntary movers respectively). Then, the average effect of training participation is given by

(12) The p-values associated with a test on the equality of means between groups are 0.000 for the trained *vs*. non trained comparison and 0.476 for the "movers" vs. "stayers" comparison.

$$\hat{\pi} = \frac{1}{N}\sum_{i=1}^{N}\left(\hat{M}_{i1} - \hat{M}_{i0}\right). \qquad [7]$$

Tables 4, 5, and 6 present maximum likelihood estimates for the three samples considered. The results from the model that treats training participation as strictly exogenous (Column 2) reproduce previous evidence based on simple correlation that receiving training reduces the probability of moving. Nonetheless, we only find that this effect is statistically significant for the whole sample and for the sample of fired workers. For the sample of voluntary movers we do not find any significant correlation between training and mobility. The predicted probabilities, shown in Table 7, indicate that training participation reduces the probability of job turnover by approximately 5.6 percentage points for those workers that have been fired. This effect is consistent with the observation typically found in the literature that training participation is negatively correlated with job mobility, reflecting the fact that employers wish to retain more highly trained workers, although our results only point to a significant negative effect for the sample of fired workers.

However, at least part of this negative correlation could be due to an endogenous training participation effect. Column 4 in Tables 4, 5, and 6, and Table 7, show that when endogeneity is accounted for, the effect of training participation becomes statistically non-significant for all the samples considered. The contrast between these two sets of estimates suggests that at least part of the negative relation between training and job mobility is due to the effect of unobserved characteristics of the trainees that are correlated with the unobserved variables that affect job mobility. In other words, once the possible spurious correlation is accounted for, we find that those who acquire training are not more likely to leave the job[13]. This result is in line with Veum's (1997), who find only limited evidence that company training reduces turnover. Therefore, we find evidence that the probability of mobility for trainees and non-trainees that does not account for the selection issue would be biased.

Regarding the rest of covariates, we obtain similar effects from exogenous and endogenous estimates. We find interesting to point out the differential effect of the variables for gender, age, and education on the probability of receiving training and on the probability of being a voluntary mover. Tenure has also a negative effect on the probability of leaving the firm, while the probability of receiving training is positively related to job tenure. As pointed out by Vaum (1997) this positive relationship is inconsistent with the human capital model, which predicts that all training should be concentrated at the start of the employment relationship. Nevertheless, it could be the case that firms delay training until there is some certainty that the cost of training can be recovered. Regarding the type of contract, those individuals with a fixed-term contract are less likely to be trained by the employer, and these individuals are precisely the ones with a higher probability of job turnover, ceteris paribus. Individuals in the public and service sectors are more likely to receive training, but there is no significant effect of these variables on the probability of moving jobs. Moreover, the size of the firm has a positive effect on training participation, although this variable is not significant at explaining job mobility. Finally, family composition is not significantly related to the acquisition of training.

(13) The estimates that do not include among the set of instruments the second language indicator are very similar, although statistically less significant.

Table 4: ESTIMATED COEFFCIENTS. TOTAL SAMPLE

	Training as exogenous ($\rho_{1\varepsilon} = \rho_{10} = 0$)				Training as endogenous ($\rho_{1\varepsilon} = \rho_{10}$)			
	(1) Training eq.		(2) Mobility eq.		(3) Training eq.		(4) Mobility eq.	
	Coeff.	t-ratio	Coeff.	t-ratio	Coeff.	t-ratio	Coeff.	t-ratio
Training			-0.432	-3.27			-0.290	-0.58
Gender and family								
Women	0.034	0.41	0.074	1.12	0.032	0.40	0.073	1.07
Married	-0.022	-0.22	0.033	0.43	-0.022	-0.21	0.033	0.42
Children	0.028	0.30	0.025	0.34	0.028	0.30	0.024	0.33
Age								
26 – 35	0.179	0.97	-0.186	-1.93	0.177	0.90	-0.187	-1.89
36 – 45	0.266	1.35	-0.384	-3.46	0.261	1.24	-0.387	-3.42
46 – 60	0.162	0.79	-0.240	-2.01	0.157	0.71	-0.241	-1.97
Education								
Upper secondary education	0.272	2.45	-0.159	-1.90	0.270	2.39	-0.163	-1.89
Tertiary education	0.487	4.90	-0.143	-1.85	0.487	4.90	-0.155	-1.80
Tenure								
4 – 6 years	0.349	2.56	-0.267	-2.61	0.354	2.39	-0.274	-2.65
7 or more years	0.358	3.17	-0.595	-6.91	0.363	3.00	-0.603	-6.44
Contract								
Temporary	-0.164	-1.31	0.686	9.64	-0.164	-1.14	0.687	9.35
Part-time	-0.399	-1.65	0.021	0.16	-0.395	-1.60	0.028	0.21
Job status								
Intermediate	-0.169	-1.33	-0.257	-1.69	-0.173	-1.37	-0.250	-1.80
Non-supervisory	-0.255	-2.16	-0.016	-0.11	-0.260	-2.29	-0.007	-0.05
Sector								
Services	0.195	2.05	-0.045	-0.65	0.196	1.94	-0.047	-0.68
Public sector	0.052	0.58	0.069	0.82	0.052	0.58	0.065	0.74
Size								
Medium	0.287	3.02	0.012	0.14	0.284	2.85	0.007	0.08
Large	0.173	1.75	-0.088	-0.88	0.171	1.71	-0.092	-0.89
Instruments								
Training in t-1	0.684	7.28	–	–	0.683	7.41	–	–
Training in t-2	0.417	4.49	–	–	0.412	4.56	–	–
Second language	0.262	2.86	–	–	0.267	2.86	–	–
Constant	-2.214	-9.69	-0.414	-2.36	-2.209	-9.53	-0.422	-2.55
Correlation coefficient (t-ratio)	–				-0.078 (-0.31)			
Log-likelihood	-1,916.14				-1,916.07			
Nº observations	2,707				2,707			

Source: Our estimations using ECHP.

Table 5: ESTIMATED COEFFCIENTS FOR FIRED WORKERS

	Training as exogenous ($\rho_{1\varepsilon} = \rho_{10} = 0$)				Training as endogenous ($\rho_{1\varepsilon} = \rho_{10}$)			
	(1) Training eq.		(2) Mobility eq.		(3) Training eq.		(4) Mobility eq.	
	Coeff.	t-ratio	Coeff.	t-ratio	Coeff.	t-ratio	Coeff.	t-ratio
Training			-0.411	-1.61			-0.487	-0.72
Gender and family								
Women	0.040	0.48	0.163	1.91	0.041	0.49	0.163	1.82
Married	-0.026	-0.25	-0.048	-0.50	-0.026	-0.24	-0.047	-0.46
Children	0.033	0.34	0.061	0.65	0.032	0.32	0.061	0.64
Age								
26 – 35	0.151	0.74	-0.081	-0.67	0.152	0.71	-0.080	-0.66
36 – 45	0.235	1.10	-0.280	-1.99	0.236	1.05	-0.278	-1.94
46 – 60	0.103	0.46	-0.012	-0.08	0.105	0.45	-0.011	-0.07
Education								
Upper secondary education	0.278	2.44	-0.241	-2.16	0.279	2.41	-0.238	-2.01
Tertiary education	0.480	4.67	-0.293	-2.69	0.480	4.66	-0.286	-2.35
Tenure								
4 – 6 years	0.358	2.53	-0.224	-1.73	0.355	2.28	-0.220	-1.65
7 or more years	0.349	2.96	-0.769	-6.38	0.346	2.69	-0.765	-5.42
Contract								
Temporary	-0.197	-1.48	0.799	8.87	-0.198	-1.28	0.797	8.55
Part-time	-0.498	-1.80	-0.231	-1.32	-0.497	-1.79	-0.234	-1.28
Job status								
Intermediate	-0.160	-1.21	-0.118	-0.45	-0.160	-1.21	-0.121	-0.57
Non-supervisory	-0.263	-2.13	0.229	0.91	-0.262	-2.18	0.224	1.09
Sector								
Services	0.207	2.09	-0.052	-0.58	0.205	1.95	-0.051	-0.55
Public sector	0.064	0.70	0.081	0.73	0.065	0.70	0.083	0.70
Size								
Medium	0.308	3.14	0.087	0.79	0.308	3.00	0.089	0.78
Large	0.173	1.69	-0.031	-0.24	0.173	1.68	-0.030	-0.21
Instruments								
Training in t-1	0.732	7.54	–	–	0.733	7.72	–	–
Training in t-2	0.393	4.11	–	–	0.393	4.22	–	–
Second language	0.212	2.17	–	–	0.212	2.15	–	–
Constant	-2.152	-8.88	-1.145	-3.44	-2.152	-8.83	-1.141	-4.71
Correlation coefficient	–				0.042			
(t-ratio)					(0.12)			
Log-likelihood	-1,373.42				-1,373.41			
Nº observations	2,398				2,398			

Source: Our estimations using ECHP.

Table 6: ESTIMATED COEFFCIENTS FOR VOLUNTARY EXITS

	Training as exogenous ($\rho_{1\varepsilon} = \rho_{10} = 0$)				Training as endogenous ($\rho_{1\varepsilon} = \rho_{10}$)			
	(1) Training eq.		(2) Mobility eq.		(3) Training eq.		(4) Mobility eq.	
	Coeff.	t-ratio	Coeff.	t-ratio	Coeff.	t-ratio	Coeff.	t-ratio
Training			-0.183	-1.16			-0.352	-0.55
Gender and family								
Women	0.029	0.35	0.008	0.10	0.031	0.38	0.009	0.10
Married	-0.033	-0.34	0.037	0.36	-0.032	-0.30	0.036	0.35
Children	0.018	0.19	-0.048	-0.49	0.017	0.18	-0.046	-0.46
Age								
26 – 35	0.206	1.03	-0.238	-1.94	0.207	0.98	-0.235	-1.85
36 – 45	0.295	1.41	-0.419	-2.91	0.297	1.33	-0.412	-2.73
46 – 60	0.191	0.88	-0.363	-2.31	0.190	0.81	-0.361	-2.20
Education								
Upper secondary education	0.263	2.31	-0.041	-0.38	0.263	2.27	-0.035	-0.31
Tertiary education	0.480	4.70	-0.088	-0.88	0.480	4.63	-0.072	-0.62
Tenure								
4 – 6 years	0.289	2.02	-0.257	-1.94	0.288	1.82	-0.249	-1.81
7 or more years	0.342	2.96	-0.547	-4.84	0.338	2.67	-0.534	-3.99
Contract								
Temporary	-0.101	-0.76	0.518	5.62	-0.099	-0.65	0.516	5.38
Part-time	-0.374	-1.50	0.089	0.52	-0.380	-1.45	0.079	0.43
Job status								
Intermediate	-0.153	-1.18	-0.316	-1.83	-0.151	-1.16	-0.325	-1.80
Non-supervisory	-0.232	-1.92	-0.136	-0.89	-0.229	-1.94	-0.148	-0.90
Sector								
Services	0.189	1.94	-0.064	-0.71	0.191	1.86	-0.060	-0.65
Public sector	0.043	0.47	-0.084	-0.72	0.043	0.46	-0.080	-0.64
Size								
Medium	0.280	2.86	0.081	0.74	0.283	2.75	0.089	0.75
Large	0.143	1.41	0.040	0.30	0.143	1.40	0.045	0.30
Instruments								
Training in t-1	0.723	7.51	–	–	0.722	7.68	–	–
Training in t-2	0.406	4.26	–	–	0.413	4.45	–	–
Second language	0.278	2.89	–	–	0.272	2.80	–	–
Constant	-2.191	-9.10	-0.730	-3.66	-2.194	-9.07	-0.721	-3.40
Correlation coefficient (t-ratio)	–				0.097 (0.28)			
Log-likelihood	-1,330.27				-1,330.21			
Nº observations	2,324				2,324			

Source: Our estimations using ECHP.

Table 7: AVERAGE ESTIMATED EFFECT OF TRAINING ON THE PROBABILITY OF JOB EXIT

	Training as exogenous	Training as endogenous
Total sample $\hat{\pi}$ (t-ratio)	-0.095	-0.066
	(-3.78)	(-0.63)
Fired workers $\hat{\pi}$ (t-ratio)	-0.056	-0.065
	(-1.96)	(-0.89)
Voluntary exits $\hat{\pi}$ (t-ratio)	-0.025	-0.045
	(-1.27)	(-0.66)

Source: Our estimations using ECHP.

5. CONCLUDING REMARKS

Understanding the relationship between on the job training and job turnover is crucial for developing appropriate human resources policies aimed at increasing the skills of employees. A common finding in this literature is that training reduces turnover. However, most of the empirical research on the effect of employer-provided training on subsequent job mobility doesn't take into account that firms provide training selectively, in the sense that employers offer training courses to those workers they wish to retain.

In this paper we argue that at least part of the negative relation between training and job mobility could be due to the characteristics of trained employees instead to a true causal effect of training on turnover. In statistical terms we argue that training could be an endogenous variable in a job mobility equation and not a strictly exogenous one. We have shown the importance of this question by the estimation of different models. Specifically, we present and compare two sets of estimates: one from a model that treats training as exogenous and another one from a model that accounts for the endogeneity of training participation.

The main conclusion that emerges from our analysis is that there is a negative effect of training participation on job mobility when the endogeneity problem is not accounted for, although it seems important to distinguish between the reasons why the worker leaves the firm. Specifically, for those workers who abandon voluntarily the firm, we do not find a statistically significant correlation between on the job training and job mobility. Only for the sub-sample of fired workers there is a statistically significant negative correlation between the two variables. Nonetheless, once we account for the possible self-selection of the trainees, the negative effect of training on job mobility disappears in all cases, and becomes statistically non-significant.

Our results that do not account neither for the endogeneity of training nor for the distinction between voluntary or involuntary exits, are in line with Parent (2003), Dearden *et al*. (1996), Loewenstein and Spletzer (1999), or Elias (1994). Nonetheless, in some of the previous works, the estimated effect is not significant [i.e. Loewenstein and Spletzer (1999)], or it is significant only for women [i.e. Elias (1994) or Lynch

(1991)]. Our results on the lack of significance of the effect of training when self-selection is accounted for is in line with Veum (1997), although our results are nor directly comparable, since he estimates a duration model and only find a significant effect for highly educated workers with more than one year of tenure. Our estimates that account for the type of exit are in line with Sieben (2007), who uses the search behavior as an indicator for the voluntary exits.

The complexity in the link between on the job training and job mobility suggests that one should be cautious when moving from the results to policy implications. According to our results, it seems crucial to take into account the potential endogeneity between these two variables, otherwise one could attribute to training an effect which is due to other unobserved characteristics of the workers and, therefore, propose misleading policy recommendations.

Our results should be complemented by further analyses. First, we have only considered binary indicators of training and mobility and analyze the impact of receiving training on the probability of moving. Nonetheless, it could be the case that it is the accumulation of training, rather than just a recent episode that affects job turnover. Moreover, another measure of job mobility that could be considered is the number of jobs an individual has held at any point in time.

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RESUMEN

Este trabajo estudia el efecto de la formación ofrecida por el empleador sobre la probabilidad de abandonar la empresa. Típicamente, la evidencia empírica muestra que la probabilidad de recibir formación en la empresa es mayor entre aquellos trabajadores con menor probabilidad esperada de salir de ella. Por lo tanto, parece que las empresas ofrecen formación selectivamente. En este trabajo se analiza empíricamente en qué medida este problema de endogeneidad produce una correlación espuria entre formación y movilidad laboral. Usando datos españoles del *European Community Household Panel*, se presentan estimaciones que ignoran este sesgo de selección y se comparan con los resultados obtenidos cuando dicho sesgo es tenido en cuenta. En general, los resultados muestran una correlación negativa entre formación y movilidad laboral, aunque sólo para los trabajadores despedidos, no para los que abandonan la empresa de manera voluntaria. Sin embargo, una vez que se tiene en cuenta el problema de endogeneidad, el efecto negativo deja de ser significativo en todos los casos.

Palabras clave: formación en el trabajo, rotación laboral, movilidad laboral.

Clasificación JEL: M53.