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IZA DP No. 3215

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December 2007

Forschungsinstitut
zur Zukunft der Arbeit
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Discussion Paper No. 3215
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ABSTRACT

Training the Unemployed in France: How Does It Affect Unemployment Duration and Recurrence?

Econometric evaluations of public-sponsored training programmes generally find little evidence of an impact of such policies on transition rates out of unemployment. We perform the first evaluation of training effects for the unemployed adults in France, exploiting a unique longitudinal dataset from the unemployment insurance system. Using the so-called timing-of-events methodology to control for both observed and unobserved heterogeneity, we find that training does not accelerate the exit from unemployment, but has a significant and positive effect on the duration of the subsequent employment spell. Accounting for training duration, we find that longer training spells cause longer unemployment spells, but also longer employment spells, suggesting that training improves the matching process between jobseekers and firms.

JEL Classification: J24, J41, J58

Keywords: training programmes, unemployment duration, multiple spells, unobserved heterogeneity

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1 Introduction

In France, the unemployment rate of low-educated workers is twice and a half the rate for workers with a post-secondary education (14.3 % versus 5.9% in 2003). In this context, training the unemployed, especially the low-skilled ones, has naturally been one of the most often implemented public policies in order to fight mass unemployment. In 1997, the European Council in Luxemburg recommended the member States to engage 20% of their unemployed workers into training programmes or other equivalent active employment programmes. France reached this objective for the first time in 2001: that year, 20,5% of unemployed workers were participating in training programmes.[1] In OECD countries, training expenditures for the unemployed represented 23% of total expenditures devoted to employment policy in 2000.[2]

This rush to training is difficult to justify on efficiency grounds, however. The vast literature evaluating its effects does not give much credit to training as an effective policy tool. In a comprehensive survey, Heckman, LaLonde and Smith (1999) point out that many empirical studies conclude that training has generally no significant impact on earnings. Recent evaluations of programmes in Sweden (Sianesi, 2007) and in Switzerland (Lalive, Van Ours and Zweimüller, 2000; Gerfin and Lechner, 2002) find very weak or even null effects of training programmes on the exit rate from unemployment.

In France, several studies have tried to evaluate public employment policies that are targeted to young unemployed workers and that have a training component. Generally theses studies find that the effect of such policies is limited (see Fougère et al. for a survey, 2000). But above all, this effect is found to depend on the individual characteristics of trainees and on the nature of the

[1] See, for instance, Plan national d'action pour l'emploi (Secrétariat Général du Gouvernement Français, 2002, p. 83).

[2] See Grubb and Martin (2001).

programme. In particular, Bonnal et al. (1997) and Brodaty et al. (2001) show that workplace training programmes in the private sector have higher effects on employment rates. However, up to now, there are no studies evaluating training programmes offered to the unemployed adults in France. This is due, mostly, to a lack of longitudinal data concerning adult unemployed workers. In addition, when such data are available, the samples are not large enough to produce precise estimates of the effects of training programmes. This paper is an attempt to carry out such an evaluation for France. For that purpose, we exploit a unique administrative data set that contains information on approximately 270,000 individual unemployment spells, and which has never been used previously for evaluating training programmes for the unemployed. This database covers the 2001-2005 period and includes usual information about the individual characteristics of the unemployed workers (age, gender, educational level, etc.). It also includes information on the individual eligibility to unemployment insurance (UI) benefits, especially the duration of the remaining period of eligibility and the amount of UI benefits at each date when unemployed.

Most of the existing studies evaluate the effect of training on the duration of the current unemployment spell, but this effect is found to be ambiguous. On the one hand, training could act as a signal towards potential employers; in that sense, it should increase- or, less presumably, decrease- the number of job offers received by the unemployed. But, on the other hand, training might also raise the reservation wage of the worker, and thus increase the duration of the current unemployment spell. Another issue, which is not often considered, is the time-dependence of the training effect. It is likely that in the short run, i.e. a few weeks after the end of the programme, training has a stimulating effect on the exit rate from unemployment. This short-term effect could result from an increase in "self-confidence" implying that training raises the unemployed's perception of his/her own employability. In the long run, i.e. after several months spent in unemployment, this impact might disappear. We address this issue by considering time-dependent effects of training *within* the current unemployment spell.

However, evaluating the impact of training on the current unemployment spell duration only is not sufficient, since the overall effect of training on the unemployment rate results from effects on both unemployment and employment spell durations. For instance, training might increase human capital, and thus raise the duration of subsequent employment spells. So it is necessary to distinguish between short-term and medium-term effects of training. Using German panel surveys, Hujer et al. (1997) and Lechner (2000) find a positive short-run effect of training on the short-run employment rate, but this effect vanishes in the long-run. Evaluating a training programme in Belgium, Cockx and Bardoulat (2000) also identify a positive short-term effect, but their data do not allow them to check the persistence of this effect. In our data set, we observe the individual employment spells following the sampled unemployment spells. Using this information, we find that training the unemployed has no significant impact on the duration of their current unemployment spell, but it increases the duration of their subsequent employment spells.

Another important finding is that the duration of training programmes should be taken into account when evaluating their impact. In the literature, little attention has been paid to the quality of training, as measured by its duration. Among a few papers, Lechner et al. (2005) find that training programmes of about two years yield substantive effects in terms of individual employment probability, but at the price of large negative lock-in effects. Similarly, we find that long training spells (more than one year) increase the duration of the current unemployment spell compared to shorter programmes, because of this lock-in effect. By contrast, long training spells have a stronger positive effect on the duration of the subsequent employment spell.

While controlled experiments are available in some countries, this is not the case in France where they are often ruled out on grounds of cost or ethical objections. When only nonexperimental data are available, Gerfin and Lechner (2002) or Sianesi (2007) have shwon that matching methods may be applied to large and rich data sets. However, such methods rely on the assumption that selection into training depends only on the values of observable covariates. Using the timing-of-events framework and the proportional hazard modelling for unemployment duration, Abbring and Van den Berg (2003) have shown that the semiparametric identification of causal parameters is possible in the presence of selectivity on unobservables. Several recent papers have implemented this strategy (Abbring et al., 2005; Lalive et al., 2000; Van den Berg et al., 2004; see also Bonnal et al., 1997, for an early model in that vein). The size of our database allows us to conduct such a flexible estimation of the impact of training, including heterogeneous and time-dependent effects. Here, effects of training are assumed to be heterogeneous since they may depend either on individual covariates such as gender and age, but also on the duration of the previous training spell (which is potentially endogenous). Assuming that training effects are time-dependent means that they may vary (either increase or decrease) over the remaining unemployment period, after the exit from the training programme.

The paper is organized as follows. The next section is devoted to a brief presentation of the French training system for the unemployed. Section 3 presents the data set. Section 4 is devoted to the statistical model that we estimate. Results are discussed in Section 5. Section 6 concludes.

2 The French public training system

The French training system for jobseekers (FTSJ hereafter) is run by three different protagonists: the State, the administrative regions and the social partners (trade unions and employers' organizations). In the FTSJ, a major distinction has to be made between the jobseekers eligible to unemployment insurance (UI) benefits, and the others. The State plays a key role, as it funds training programmes for the long-term unemployed who have exhausted their rights to UI, as well as for welfare recipients. It also provides revenues to jobseekers who are not eligible to UI and who get through State-appointed training programmes. These revenues are labelled "*Régime de Stagiaire Public*" (RSP hereafter). Besides, the State offers training both to the eligible and non-eligible unemployed through the French public employment service, *Agence Nationale pour l'Emploi* (ANPE hereafter), a mission that was reinforced in 2001 in the framework of the PARE ("*Plan d'Aide au Retour à l'Emploi*") reform. Thus, since this reform, the French public employment service is the obliged spot for a jobseeker willing to enter a public training programme.

Theoretically, the administrative regions have much power for funding jobseekers' training since the decentralization Laws launched in 1983. In practice, however, the State is still the principal decision-maker when it comes to prescribing training measures.[3] In contrast, the role of the social partners, which manage the institution in charge of the payment of UI benefits, called "*Union nationale interprofessionnelle pour l'emploi dans l'industrie et le commerce*" (UNEDIC hereafter), has been thoroughly reinforced since the 2001 reform. Before this date, the role of UNEDIC was to provide the UI recipients who got trained with a benefit called "*Allocation Formation Reclassement*" (AFR hereafter), which was constant over time and which acted as a substitute for the decreasing UI

[3] See Marimbert and Joly (2004).

benefits then granted to regular UI recipients. Though paid by UNEDIC, this AFR benefit was mainly funded by the State (which accounted for 80% of the AFR before 1997, and 41 % between 1997 and 2001). Since the PARE reform set up in 2001, UNEDIC now funds integrally the benefits of those trainees eligible to UI. These benefits are now called "*Allocation de retour à l'emploi-formation*" (AREF hereafter). Besides, UNEDIC and its local agencies, called "*Association pour l'emploi dans l'industrie et le commerce*" (ASSEDIC hereafter), are now in charge of prescribing and buying training courses. In particular, ASSEDIC agencies are in charge of buying training programmes that:

- either respond to local needs for skills in preliminarily identified economic activities,
- or provide the jobseeker with skills for a specific job, for which an employer has committed to hire the unemployed worker at the end of the training period.

In our sample, only 10 % of the unemployment spells are associated with participation to a training programme. Although it concerns a limited number of persons, the total cost of training, including courses and benefits payment for the trainees, represented 3,35 billion euros in 2003.

To simplify, we could say that the State cares about the most needy peole (especially the long-term unemployed), whereas UNEDIC is in charge of UI recipients who have potentially a higher employability. The administrative regions express their needs for skills at the local level to ASSEDIC agencies and to the public employment service, and they are also in charge of the funding. Our data set covers the 2001-2005 period. A strong reason for considering this period only is that between 1993 and 2001, the time profile of UI benefits was decreasing over the unemployment period (it is constant since the 2001 reform). However, for those unemployed workers who entered a training programme, the

UI benefits remained constant until the programme stopped. Hence, the system was providing an incentive to enter a programme, whatever the quality of the training programme. By reintroducing a constant benefit over the whole period of eligibility to UI, the PARE reform removed this feature. For this reason, we focus in this paper on the analysis of unemployment spells beginning between 2001 and 2005.

3 Data and descriptive analysis

Our empirical analysis makes use of data extracted from the "*Fichier National des Assedic*" (FNA hereafter) collected by UNEDIC. The FNA file contains information on all the workers entering unemplyment and who are either UI or welfare recipients. This is due to the fact that UNEDIC is in charge of paying UI and welfare benefits.

The sample has been drawn randomly from the FNA file. More precisely, our sample is made of one unemployed out of forty entered into the FNA file between July 2001 and December 2005. For each individual, the extracted file contains precise information on all the unemployment spells that could have occurred since 1993. The sample mixes information collected by UNEDIC, which is in charge of paying the unemployed their benefits, and by the ANPE (i.e. the public employment service), which role is to counsel the unemployed for their search activities and to monitor them. It contains the dates at which workers are registered and deregistered as unemployed by the public employment service, as well as the start and termination dates of UI eligibility periods. Information about the nature of the benefits makes it possible to identify training spells from regular unemployment spells. More precisely, an individual who is eligible to UI benefits is registered as a trainee whenever he/she receives AREF benefits. If he/she is not eligible to UI benefits, then he/she receives RSP benefits during the training period. Defining a training period by the nature of the benefits, we can identify the dates of entry into and exit from a training programme. The sample we use includes 270,139 spells, among which 19,673 spells are associated with at least one training period.

Moreover, we observe the following individual covariates: gender, nationality, educational level, skill level of the last job, type of the labor contract in the last job (i.e .short-term or long-term), cause of entry into unemployment, cumulated duration of unemployment over the past two years, number of previous unemployment spell (from 1993), amount of the UI benefit, level of the last wage (if any), and remaining duration of eligibility to UI benefits at each instant of the current unemployment spell .

Entry into and exit from unemployment are recorded on a daily basis, so that we model duration in continuous time. In our evaluation, we consider training partly as a separate state. This means that we model explicitly transitions from unemployment to training and from training back to unemployment,[4] but we assume that the duration of the current unemployment spell is augmented by the time spent in all training spells that occur during this unemployment spell. This allows us to examine directly the impact of the previous occurrence of a training programme on the transition rate from unemployment to employment, whatever the time already spent in the current unemployment spell. In other words, any observed unemployed spell starts with a transition from employment to unemployment and it ends with the first subsequent transition to employment (it is right-censored if no transition to employment is observed). Hence, in our modelling, transitions may occur from unemployment to employment, from unemployment to training, from training to employment and from employment to unemployment. We do not consider transitions from employment to training, as people must stay at least a few days unemployed before getting into a training

[4]In our data set we observe no direct transitions from training to employment

programme offered to unemployed workers. An employment spell starts with a transition from unemployment to employment. The duration of an employment spell is complete when the individual reenters unemployment. Yet, it is unclear whether the person stays employed without interruption or not. So it is proper to consider that we measure unemployment recurrence, rather than employment duration.

Table 1 indicates that assignment to training is certainly not random. Women receive training more often than men. Training occurrence increases with the educational level, and it is higher for French people than for foreigners. Training is also more often provided to younger individuals. Finally, having experienced other unemployment spells in the past two years decreases the probability of being trained.

Figure 1 displays the empirical survival functions of unemployment spell durations for both trainees and non-trainees over the 2001-2005 period. There we consider as trainees those individuals who experienced at least one training spell during their unemployment spell. The survival functions of trainees' unemployment spell durations are estimated both when these unemployment spells include and do not include the durations of the training spells experienced by the trainees over their unemployment spell. Figure 1 shows that trainees have a higher probability of surviving in unemployment than non-trainees. However, when the duration of training spells is not counted, the survival function of trainees gets closer to the survival function of non-trainees. Thus, the difference between survival functions of these two groups can be partly explained by a lock-in effect, corresponding to a decrease in the individual search effort during training. The remaining part of the gap between estimated survival functions of trainees and non-trainees may result from differences in observable and unobservable individual heterogeneity. In particular, the assignment process to training could give priority to the less employable individuals. Although there is empirical evidence of some "cream-skimming" in the assignement process to training programmes in other countries,[5] the hypothesis of a "negative" selectivity bias in the French system is quite realistic, since French public employment policies are generally targeted towards the less employable workers. By contrast, Figure 2 shows that trainees have a higher probability to stay employed than non-trainees. Whether this is due to a selection effect or to a positive causal effect of training is yet unclear, and is a case for a deeper analysis.

4 Evaluating training with a multiple-spells duration model

As for most active labor market policies, assignment to training programmes is likely to be endogenous, as it is based on the caseworker's decision and on the worker's agreement. Both decisions depend on observed and unobserved (by the econometrician) characteristics. As shown by Abbring and Van den Berg (2003), a statistical duration model makes it possible to identify separately the causal effect of training on the subsequent unemployment duration, and the distribution of unobserved characteristics. Abbring and Van den Berg (2003) provide identification conditions for the mixed proportional hazards model. Their identification proof is nonparametric in the sense that no functional form is assumed for the baseline hazard functions and for the multivariate distribution of unobserved heterogeneity terms. Abbring and Van den Berg show that the elapsed duration until training contains useful information to identify the causal effect of training from the effect induced by selection on observables and unobservables. A competing-risks duration model, in which transitions from un-

[5]See, for instance, Barnow (2000) for an analysis of the Job Training Partnership Act in the U.S.

employment to training are distinguished from transitions from unemployment to employment, may be used to identify the joint distribution of unobservables. The duration of the unemployment spell which occurs directly after the end of the training spell identifies the causal effect of the treatment. The exact timing of events is important since the causal effect is revealed by the change in the unemployment-employment transition rate that occurs once treatment is received (if the treatment is effective). This can be distinguished from the effect of unobserved heterogeneity because the latter is assumed constant over a spell. In contrast, if unobserved shocks occur along the spell and if their timing is correlated with that of treatment, identification fails. Identification requires also that the duration until treatment varies sufficiently. Indeed, Figure 3 shows that, in our data set, the nonparametric estimate of the aggregated rate of transition from unemployment to the first training spell is quasi-constant over the unemployment spell.[6]

Our statistical model is based on the framework introduced by Abbring and Van den Berg (2003), but it is extended to account for training spell durations and unemployment recurrence. When unemployed, workers may move either to training or to employment. The causal effect of training is defined as a shift in the individual transition rate towards employment, once treatment has occurred. This effect is assumed to depend on observed individual characteristics. It may also vary with the elapsed duration since entry into training and with the duration of the training period. On the whole, we consider three types of transitions: transitions from unemployment to employment, transitions from unemployment to training, transitions from training to unemployment, and transitions from employment to unemployment.

[6] For that nonparametric estimation, spells that end with a transition from unemployment to employment and that do not contain at least one training spell are treated as right-censored observations.

4.1 Transitions from unemployment

Let us denote η_{UE} the transition rate from unemployment to employment, and η_{UT} the transition rate from unemployment to training. These transition rates are assumed to be generated by mixed proportional hazards (MPH) models (see, for instance, Lancaster, 1990). Let x be a vector of observable covariates, while v_{UE} and v_{UT} are the unobserved random terms that affect transitions from unemployment to employment and from unemployment to training, respectively.

For an unemployed worker who has been trained during t_T periods and who spent t_B periods in the current unemployment spell before entering the first training period observed within the current unemployment spell, the conditional transition rate from unemployment to employment is supposed to be:

$$\begin{aligned}
&\eta_{UE}(t \mid x, t_B, t_T, v_{UE}) \\
&\quad = \psi_{UE}(t) \exp\{x\beta_{UE} + v_{UE}\} \times \mathbf{1}(t < t_B) \\
&\quad + \psi_{UE}(t) \exp\{x\beta_{UE} + v_{UE} + [\alpha_U(t_T) + \beta_U(t - t_T - t_B) + \gamma_U(x)]\} \\
&\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad \times \mathbf{1}(t > t_B + t_T)
\end{aligned}$$

where $\psi_{UE}(t)$ is the baseline transition rate from unemployment to employment and where the term $[\alpha_U(t_T) + \beta_U(t - t_T - t_B) + \gamma_U(x)]$ represents the causal effect of training on the transition rate from unemployment to employment. The function $\alpha_U(t_T)$ captures the potential effects of the (cumulated) time t_T already spent in training on this transition rate, while the function $\gamma_U(x)$ represents the treatment effect for different values of individual covariates x (these effects are typically captured by interaction terms between x and the dummy variable indicating that a training spell has occurred). The function $\beta_U(t - t_T - t_B)$, where $(t - t_T - t_B)$ represents the time elapsed since the end of the last training period, accounts for a short-term effect of training which is potentially different from the medium-term effect. The intuition is that training may act as a stimulus during the few weeks following the end of the training period, without having any long-lasting impact on the individual's ability to find a job. This specification accounts for the fact that the exit rate from unemployment to employment is zero while in a training spell.

If the unemployed worker re-enters unemployment after the first training spell, her exit rate to unemployment becomes :

$$\begin{aligned}&\eta_{UE}\left(t \mid x, t_B, t_T, v_{UE}\right)\\&\quad= \psi_{UE}\left(t\right)\exp\left\{x\beta_{UE} + v_{UE} + \left[\alpha_U\left(t_T\right) + \beta_U\left(t - t_T - t_B\right) + \gamma_U(x)\right]\right\}\\&\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\text{for } t > t_B + t_T\end{aligned}$$

If the unemployed worker experiences a second training spell, her transition rate from unemployment to employment at the end of this second training spell is still :

$$\begin{aligned}&\eta_{UE}\left(t \mid x, t_B, t_T, v_{UE}\right)\\&\quad= \psi_{UE}\left(t\right)\exp\left\{x\beta_{UE} + v_{UE} + \left[\alpha_U\left(t_T\right) + \beta_U\left(t - t_T - t_B\right) + \gamma_U(x)\right]\right\}\\&\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\text{for } t > t_B + t_T\end{aligned}$$

where t_T denotes now the total time spent in training during the current unemployment spell, and t_B is the duration of the current unemployment spell (not including the duration of training periods) at the date of entry into the second training spell.

In France, the process of allocating job seekers to training is characterized by substantial heterogeneity. Thus it is likely that participants and nonparticipants differ with respect to covariates and unobservables that jointly determine unemployment duration and participation in training. To deal with this problem, we characterize the nonrandom nature of this selection process by specifying the transition rate from unemployment to training by:

$$\eta_{UT}\left(t \mid x, v_D\right) = \psi_{UT}\left(t\right) \exp\left(x\beta_{UT} + v_{UT}\right)$$

where $\psi_{UT}\left(t\right)$ is the baseline transition rate from unemployment to training and β_{UT} is the vector of slope parameters that are associated with the observable covariates x.

Modelling jointly the transition rates η_{UE} and η_{UT} implies that we rule out any *anticipation effect* of the training programme. This absence of anticipation is a necessary condition to identify the causal effect of training by the *timing-of-events* method (Abbring and Van den Berg, 2003). Such an anticipation effect arises when the realisation of the date of entry into training has an impact on the transition rate to employment *before* this date of entry. This may occur if the unemployed worker either knows or can anticipate the date of entry into training and thus lowers her job search intensity before training starts. In the French training system, however, such a systematic anticipation is unlikely because there is no statutory date beyond which training or another active labor market programme becomes mandatory. Another cause of anticipation could result from the fact that a significant amount of time elapses between the date when the training is decided and the actual beginning of the training programme, which could result from the rationing of training vacancies. The only study describing the training participation process in France (Fleuret, 2006) yet shows that such waiting periods are quite short and should not invalidate our "no anticipation" assumption.

4.2 Transitions from training

When being trained, individuals may move either to unemployment or to employment. However, in our data set, we observe no direct transitions from training to employment. Thus we set to zero the transition rate from training to employment. Note that the duration of a training spell is chosen both by the unemployed worker and by the caseworker *prior* to the beginning of the training period. Hence the process of exiting the training programme should not be driven by the behavior of the unemployed worker, except in the case where she decides to stop the programme before its termination. Unfortunately, our data do not allow us to observe early exits out of training. Let us also remark that, in our data, a training spell may result from the participation in successive and different training programmes. Since we do not observe the dates of entry and exit in each programme, we are obliged to define a training spell as the number of successive months spent in training, without interruption. These different arguments lead us to assume that the training spell durations are randomly distributed.

Thus we account for potentially varying training durations by specifying the transition rate η_{TU} from training to unemployment as:

$$\eta_{TU}\left(t \mid x, v_{TU}\right) = \psi_{TU}\left(t\right) \exp\left(x\beta_{TU} + v_{TU}\right)$$

where $\psi_{TU}\left(t\right)$ is the baseline transition rate from training to unemployment, β_{TU} is the vector of slope parameters that are associated with the observable covariates x, and v_{TU} is the unobserved random term that affects the individual transition rate from training to unemployment.

In our data set, we observe also that a given unemployment spell may include several training spells. For instance, we can observe an individual path composed of a first unemployment subspell, followed by a first training spell, itself followed by a second subspell of unemployment, preceding a second training spell, followed successively by a third unemployment subspell, an employment spell, and finally a return to unemployment. To take into account training recurrence without complicating too much the statistical analysis, we assume that:

1. the transition rate η_{TU} from training to unemployment is the same in each training spell; it depends neither on the number of past training spells, nor on the total time spent in previous training spells;

2. the transition rate η_{UE} from unemployment to employment is only affected by the cumulated duration of previous training spells (i.e. by the total time spent in training within the current unemployment spell), and not by their number.

4.3 Transitions from employment

Let us recall that we consider as an "employment" spell a spell that begins with a transition from unemployment to employment and that ends with a re-entry into unemployment (see Section 3). Thus the duration of such a spell is known when the worker reenters unemployment, otherwise the spell is treated as right-censored. The transition rate from employment to unemployment is defined as:

$$\eta_{EU}\left(t \mid x, v_{EU}\right) = \psi_{EU}\left(t\right) \exp\left(x\beta_{EU} + \left[\alpha_E\left(t_F\right) + \gamma_E(x)\right]T + v_{EU}\right)$$

where $\psi_{EU}\left(t\right)$ is the baseline transition rate from employment to unemployment, β_{EU} is the vector of slope parameters that are associated with the observable covariates x, and v_{EU} is the unobserved random term that affects the individual transition rate from employment to unemployment. There again the term $\left[\alpha_E\left(t_F\right) + \gamma_E(x)\right]$ captures the causal effect of training on the duration of the subsequent employment spell. The dummy variable T equals one if the worker has previously participated in one training programme (at least), 0 otherwise. The function $\alpha_E(t_F)$ captures the potential effects of the total time spent in training on this duration, while the function $\gamma_E(x)$ measures the effect of training interacted with different values of individual covariates x. For individuals who are observed to move from unemployment to employment, the likelihood involves an additional term which is the likelihood of the (potentially right-censored) duration of the subsequent employment spell.

4.4 Specification issues

Our model involves four types of transitions. The specification of the joint distribution of the corresponding heterogeneity terms is therefore an important aspect of our approach. In practice, estimating the joint distribution of unobserved heterogeneity with a completely flexible covariance matrix could be difficult. Hence, for simplification, this distribution is supposed to be generated by a two-factor loading model; in other terms, we assume that each unobserved random term depends on two fundamental factors V_1 and $V2$. This assumption implies that:

$$v_k = \exp(\alpha_k^1 V_1 + \alpha_k^2 V_2)$$

with $k = \{U, E, T\}$. As shown by Heckman and Singer (1984), the estimates may strongly depend on the distribution of these two common factors. Thus our strategy is to consider various distributions for these tow random variables and to select the more appropriate using the Vuong test (see the Appendix for a brief presentation of this test).

First we consider that each unobserved factor has a discrete distribution with two mass points. More precisely V_1 and V_2 are assumed to be both distributed on the support $\{-1; 1\}$ with distinct probabilities. This specification can be directly estimated by a maximum likelihood procedure. But we also consider continuous parametric distributions such as the normal and the beta distributions, and a mixture of two normal distributions. In each of these cases, the model is estimated using the simulated maximum likelihood method.

The explanatory variables we consider include gender, French nationality, the educational level, the skill level of the previous job, the labor contract in the previous job (i.e. a short-term vs. a long-term contract), the level of the previous wage, the cause of entry into unemployment (layoff, quit, or termination of a short-term labor contract), the individual unemployment history (his/her cumulated unemployment duration in the past two years), the individual unemployment recurrence (the number of previous unemployment spells during the past two years), the UI benefit level (if the unemployed worker is still eligible to UI), and the remaining duration of eligibility to UI. We adopt a piecewise constant hazard for the baseline functions $\psi_{jk}(t)$:

$$\psi_{jk}(t) = \sum_{l=1}^{L} e^{\psi_{jkl}}.\mathbf{1}(t \in I_l)$$

For unemployment and employment durations, we consider eight intervals I_l, each being 90 days long. In other terms, $I_1 = [1, 90]$, $I_2 = [91, 180]$, $I_3 = [181, 270]$, $I_4 = [271, 360]$, $I_5 = [361, 450]$, $I_6 = [451, 540]$, $I_7 = [541, 630]$ and $I_8 = [631, \infty)$. For the time spent in training, we consider four intervals of 90 days each. The sample likelihood function is derived from the form of the generic likelihood of a multiple-states transition model (see, for instance, Fougère and Kamionka, 2005). Because local maxima are likely to occur, we run the optimization procedure several times with randomly chosen starting values. The tolerance for the gradient is set to 10^{-6} and we use the Gauss Optmum library (with the BFGS algorithm in order to deal with the large numbers of observations and parameters). Out of ten sets of random starting values, nine have converged to the same maximum, and only one has converged to another set of parameters, corresponding to a lower likelihood function. Thus we may be quite confident in the validity of the reported estimates, which are likely to be associated with the global maximum of the likelihood function.

5 Estimates

In order to choose the most appropriate specification, we apply the Vuong (1989) test to the estimated models. Table 2 provides the results of this test for the five specifications that we consider: it turns out that the best specification is the binomial distribution. Therefore we present only the results obtained under this distributional assumption.

5.1 Effects of the covariates

Table 3 shows the estimated effects of elapsed duration and individual characteristics on the transition rate from unemployment to employment. This transition rate is higher for recurrent unemployed, i.e. those having more frequently entered unemployment over the past two years. Coherently, it is higher for workers who do not receive unemployment benefits and for those who were previously employed in a temporary job (with a short-term labor contract). Older individuals, as well as persons with a high cumulated unemployment duration (corresponding to the total time spent in unemployment over the past two years), have a lower transition rate to employment. These results suggest that there are (at least) two distinct groups of unemployed people, the first one being composed of young workers and/or recurrent unemployed who move more rapidly from unemployment to employment, the second including older workers and/or previously long-term unemployed who are characterized by a low exit rate from unemployment.

Table 4 reports the estimated effects of individual characteristics on the transition rate from unemployment to training. Unemployment recurrence speeds up entry into training, and so does training accumulation (i.e. the total time spent in training). Unemployed workers living in high unemployment districts have a higher transition rate to training, which can be interpreted as a supply-side effect since public budgets for training are often higher in such areas. The rate of entry into training increases with the remaining duration of eligibility to UI insurance; this means that, for unemployed people who are eligible to UI, it is higher at the beginning of the period of eligibility to UI. However, it is lower for unemployed who receive no unemployment benefits.

Table 5 reports the estimated effects of individual covariates on the transition rate from training to unemployment. It shows that people benefiting from longer periods of eligibility to UI benefits experience longer training spells. It is also the case for low-educated people.[7]

Finally, Table 6 shows the estimates parameters of the transition rate from employment to unemployment. The less educated and/or less skilled workers experience shorter employment spells. Moreover, the transition rate out of employment decreases with age, but is higher in districts characterized by a higher unemployment rate.

5.2 Causal effects of training

5.2.1 Effects on unemployment spell durations

Table 7 reports the estimated effects of training on the exit rate from unemployment. Due to the incorporation of interaction terms, these effects depend on the values of individual exogenous covariates. Table 7 also reports the estimated parameters of the model without unobserved heterogeneity. It appears

[7] This may result from the fact that those people have a better access to longer training programmes.

that this latter model (corresponding to the assumption of a selection on observables only) is misleading. When unobserved heterogeneity is not taken into account, training occurrence is found to have a positive and significant impact on the duration of unemployment: the trainees' transition rate to employment would increase by about 66% ($exp(0.507)-1$) when training is completed. Introducing correlated unobserved heterogeneity terms affects strongly this estimate: the transition rate of trainees decreases by roughly 2% ($exp(0,020) - 1$) under the most appropriate specification, i.e. the binomial distribution. This effect becomes even more negative over time: six months after the end of the training spell, the transition rate falls by 14% compared to the period just after training. These results suggest that training may act as a stimulus during a few weeks only, which could be due to an increase in individual "self-confidence". In the medium term, i.e. after several months of subsequent unemployment, this impact turns into a negative one, presumably because of the increasing discouragement of unemployed workers.

Another important finding is that longer training programmes cause a larger decrease in the transition rate from unemployment to employment. For instance, training spells between 4 and 8 months decrease this transition rate by about 34%, relatively to shorter training spells.

Finally, while the effect of training is the same for both genders, it turns out that persons with a lower educational level are those who benefit most from training. Training is also more efficient for young people, as the transition rate of trainees below 25 is 20% higher than the one of trainees above this age.

5.2.2 Effect on unemployment recurrence

Regarding the effect of training on the transition rate from employment back to unemployment, we also observe differences between the models with or without unobserved individual heterogeneity. Without unobserved heterogeneity, the effect of training is negative but small: it decreases this transition rate by about 8% (see Table 8). When allowing for correlated unobserved heterogeneity, the effect of training is stronger: it decreases the transition rate to unemployment by 21% (see Table 8).

Besides, the impact of past training spells depends strongly on their duration. Once the individual has found a job, training spells which lasted more than one year decrease the re-entry rate into unemployment by more than 38%, relatively to training spells which lasted less than four months.

Interactions between individual covariates and the past occurrence of a training spell appear to have no significant effect on the transition from employment to unemployment. It is likely that, for estimating precisely such interactions, we should observe much more employment spells with past training occurrence in our sample.

5.3 Estimating the net effect of training

The parameters associated with the endogenous regressor indicating the occurrence of a past training spell cannot be interpreted as the net effect of training. When heterogeneous effects are significant, this net effect also depends on the distribution of exogenous covariates. To measure the average impact of training on individual trajectories of adult unemployed, we thus rely on a simulation based on the estimated parameters of the model. These parameters make it possible to attribute to each observation a sequence of durations that do not correspond to the observed durations, but are generated by the estimated model. More precisely, let us denote $t_U^s(1)$, t_T^s, $t_E^s(1)$ the simulated durations in unemployment, training and employment, respectively . Then we simulate counterfactual durations $t_U^s(0)$ and $t_E^s(0)$ by setting the parameters associated with training to zero. In this counterfactual exercise, the simulated duration spent in training t_T^s (if any) is kept the same, since the parameters of the transition from training to unemployment are not modified. This allows us to calculate the average remaining duration in unemployment, when training has a non-null vs. a null effect on the exit rate from unemployment. We do the same for simulating the average global effect of training on employment spell durations.

The results of this simulation exercise are presented in Table 9. The simulations are conducted by using the parameter estimates of the best specification, i.e. the binomial distribution for the unobserved heterogeneity terms.[8] Table 9 shows that training contributes to lengthening unemployment spells (+93 days on average), but also subsequent employment spells (+336 days on average). Can the negative impact of training on the unemployment spell duration be interpreted as a strong lock-in effect? Do trainees experience longer unemployment spells because their transition rate out of unemployment decreases sharply during training, or because of the negative ex-post effect of training ? To answer this question, we compare the effect on the mean unemployment spell duration (+93 days) with the average simulated duration of training spells (+94 days). This comparison suggests that the whole negative impact of training on the current unemployment spell duration results from the lock-in effect. Training spells which occurred early in the previous unemployment spell (i. e. those that started in the first three months of unemployment) have a larger impact: they increase by 376 days the mean duration of the subsequent employment spell, while those starting later (typically, after the sixth month in unemployment) increase by 313 days this average duration. This result cannot be explained by the duration of training spells offered in the first three months of unemployment: the correlation coefficient between the time spent in unemployment

[8]Note that the results of this simulation exercise do not strongly depend on the choice of the unobserved heterogeneity distribution.

before entry in the first training spell and the duration of this first training spell being equal to -0.08265 (in the trainees' subsample), the training spells offered in the first three months are not longer on average than those offered later in the unemployment spell.

6 Conclusion

In this paper we have carried out the first econometric evaluation of the effects of training programmes designed for the unemployed adults in France. Using the so-called "timing-of-events" methodology to control for both observed and unobserved individual heterogeneity, we find that training does not accelerate the exit rate from unemployment, which is in line with most previous studies devoted to this issue. A rather new finding consists in the positive and statistically significant effect of training on the duration of the subsequent employment spell. This effect depends on the duration of the past training spell too, but in the opposite sense: longer training spells are associated with longer employment spells. This is in line with the idea that training increases individual human capital and improves the matching process between firms and jobseekers, helping them to find jobs which are better suited to their skills.

Appendix

The Vuong test

The Vuong test (Vuong, 1989) is based on the Kullback-Leibler information criteria (KLIC), a measure of the "distance" between two statistical models. Vuong (1989) defines the KLIC as:

$$KLIC \equiv E_0 \left[\ln h_0 \left(Y_i \mid X_i \right) \right] - E_0 \left[\ln f \left(Y_i \mid X_i ; \beta_* \right) \right]$$

where $h_0(. \mid .)$ is the true conditional density of Y_i given X_i (that is, the true but unknown model), E_0 is the expectation under the true model, and β_* are the pseudo-true values of β (the estimates of β when $f(Y_i \mid X_i)$ is not the true model). The best model is the model that minimizes the equation given above, for the best model is the one that is closest to the true, but unknown, specification. In other terms, the model that is closest to the true specification is the model that maximizes $E_0[\ln f(Y_i \mid X_i; \beta_*)]$.

More precisely, the null hypothesis of Vuong's test is

$$H_0 : E_0\left[\ln \frac{f(Y_i \mid X_i; \beta_*)}{g(Y_i \mid X_i; \gamma_*)}\right] = 0$$

which states that the two models f and g are equally close to the true specification. The expected value in the above hypothesis is unknown. Vuong demonstrates that under fairly general conditions,

$$\frac{1}{n} LR_n\left(\widehat{\beta}_n, \widehat{\gamma}_n\right) \overset{a.s.}{\to} E_0\left[\ln \frac{f(Y_i \mid X_i; \beta_*)}{g(Y_i \mid X_i; \gamma_*)}\right]$$

which means that the expected value can be consistently estimated by $\frac{1}{n}$ times the likelihood ratio statistic. The actual test is then

$$\text{under } H_0 : \frac{LR_n\left(\widehat{\beta}_n, \widehat{\gamma}_n\right)}{\sqrt{n}\widehat{\omega}_n} \overset{d.}{\to} N(0,1)$$

where

$$LR_n\left(\widehat{\beta}_n, \widehat{\gamma}_n\right) \equiv L_n^f\left(\widehat{\beta}_n\right) - L_n^g\left(\widehat{\gamma}_n\right)$$

and

$$\widehat{\omega}_n^2 = \frac{1}{n}\sum_{i=1}^{n}\left[\ln \frac{f\left(Y_i \middle| X_i; \widehat{\beta}_n\right)}{g\left(Y_i \middle| X_i; \widehat{\gamma}_n\right)}\right]^2 - \frac{1}{n}\left[\sum_{i=1}^{n} \ln \frac{f\left(Y_i \middle| X_i; \widehat{\beta}_n\right)}{g\left(Y_i \middle| X_i; \widehat{\gamma}_n\right)}\right]^2$$

The Vuong test can be described in simple terms. If the null hypothesis is true, the average value of the log-likelihood ratio should be zero. If H_f is true, the average value of the log-likelihood ratio should be significantly greater than zero. If the reverse is true, the average value of the log-likelihood ratio should be significantly less than zero.

The log-likelihoods used in the Vuong test are affected if the number of parameters in the two models estimated is different, and therefore the test must be corrected for the degrees of freedom. Vuong (1989) suggests using a correction that corresponds either to Akaike's (1973) information criteria or Schwarz's (1978) Bayesian information criteria. The expression of the latter is:

$$\widetilde{LR}_n\left(\widehat{\beta}_n, \widehat{\gamma}_n\right) \equiv LR_n\left(\widehat{\beta}_n, \widehat{\gamma}_n\right) - (p-q)\,\frac{\ln n}{2}$$

where p and q are the number of estimated parameters in models f and g, respectively.

References

Abbring, Jaap H. and Gerard J. Van den Berg. 2003. "The Non-Parametric Identification of Treatment Effects in Duration Models." *Econometrica* 71:1491-1517.

Abbring, Jaap H., Gerard J. Van den Berg and Jan Van Ours. 2005. "The Effect of Unemployment Insurance Sanctions on the Transition Rate from Unemployment to Employment." *The Economic Journal* 115(505):602-30.

Akaike, Hirotsugu. 1973. "Information Theory and an Extension of the Likelihood Ratio Principle." In *Second International Symposium of Information Theory*, eds. B. N. Petrov and F. Csaki, 257-81. Budapest: Akademinai Kiado.

Barnow, Burt S. 2000. "Exploring the Relationship between Performance Management and Program Impact: A Case Study of the Job Training Partnership Act." *Journal of Policy Analysis and Management* 19(1):118-41.

Bonnal, Liliane, Denis Fougère and Anne Sérandon. 1997. "Evaluating the Impact of French Public Employment Policies on Individual labor Market Histories." *The Review of Economic Studies* 64(4):683-713.

Brodaty, Thomas, Bruno Crépon and Denis Fougère. 2001. "Using Kernel Matching Estimators to Evaluate Alternative Youth Employment programmes : Evidence from France 1986-1988." In *Econometric Evaluations of Labor Market Policies*, eds M. Lechner and F. Pfeiffer, 85-124. Heidelberg: Physica Verlag.

Cockx, Bart and Isabelle Bardoulat. 2000. "Vocational Training: Does it Speed the Transition Rate out of Unemployment?" Tinbergen Institute Discussion paper No. 00-016/3, Amsterdam.

Fleuret, Aurore. 2006. "L'orientation des chômeurs vers la formation de 2002 à 2004." DARES Premières synthèses No. 29-2, Paris.

Fougère, Denis and Thierry Kamionka. 2005. "Econometrics of Individual Labor Market Transitions", IZA Discussion paper No. 1850, Bonn. Forthcoming in *The Econometrics of Panel Data*, eds L. Matyas and P. Sevestre, 3rd edition. Berlin: Springer.

Fougère, Denis, Francis Kramarz and Thierry Magnac. 2000. "Youth Employment Policies in France." *European Economic Review* 44(4-6):928-42.

Gerfin, Michael and Michael Lechner. 2002. "A Microeconometric Evaluation of the Active labor Market Policy in Switzerland.". *The Economic Journal* 112(482):854-93.

Grubb, David and John P. Martin. 2001. "What Works and for Whom: A Review of OECD Countries Experiences with Active labor Market Policies." OECD Working paper No. 2001-14, Paris.

Heckman, James J., Robert J. LaLonde and Jeffrey A. Smith. 1999. "The Economics and Econometrics of Active Labor Market programmes." In *Handbook of Labor Economics*, eds A. Ashenfelter and D. Card, Vol.3A, 1865-2097. Amsterdam: Elsevier.

Hujer, Reinhardt, Kai-Oliver Maurer and Marc Wellner. 1997. "The Impact of Unemployment Duration in West Germany. Combining a Discrete Hazard Rate Model with Matching Techniques." Frankfurter Volkswirtschaftliche Diskussionsbeiträge No. 74, Johann Wolfgang Goethe-University, Frankfurt am Main.

Lalive, Rafael, Jan Van Ours and Josef Zweimüller. 2000. "The Impact of Active Labor Market programmes and Benefits Entitlement Rules On the

Duration of Unemployment." IZA Discussion Paper No. 149, Bonn.

Lechner, Michael. 2000. "An Evaluation of Public Sector Sponsored Continous Vocational Training programmes in East Germany." *The Journal of Human Resources* 35(2):347-75.

Lechner, Michael, Ruth Miquel and Conny Wunsch. 2005. "Long-Run Effects of Public Sector Sponsored Training in West Germany." CEPR Discussion Paper No. 4223, London.

Marimbert, Jean and Benjamin Joly. 2004. *Le rapprochement des services de l'emploi : rapport au Ministre des affaires sociales, du travail et de la solidarité.* Paris: La Documentation Française.

OECD. 2003. *Employment Outlook 2003.* Paris: OECD.

Schwarz, Gideon. 1978. "Estimating the Dimension of a Model." *The Annals of Statistics* 6(2):461-64.

Secrétariat Général du Gouvernement Français. 2002. *Plan national d'action pour l'emploi.* Paris: La Documentation Française.

Sianesi, Barbara. 2007. "Differential Effects of Active Labor Market programmes for the Unemployed." *Labour Economics,* forthcoming.

Van den Berg, Gerard J., Bas Van der Klaauw and Jan Van Ours. 2004. "Punitive Sanctions and the Transition Rate From Welfare to Work." *Journal of Labor Economics* 22(1):211-41.

Vuong, Quang H.. 1989. "Likelihood Ratio Tests for Model Selection and Non-Nested Models." *Econometrica*, 57(2):307-33.

Figure 1: Kaplan-Meier estimates of survival functions of unemployment spell durations

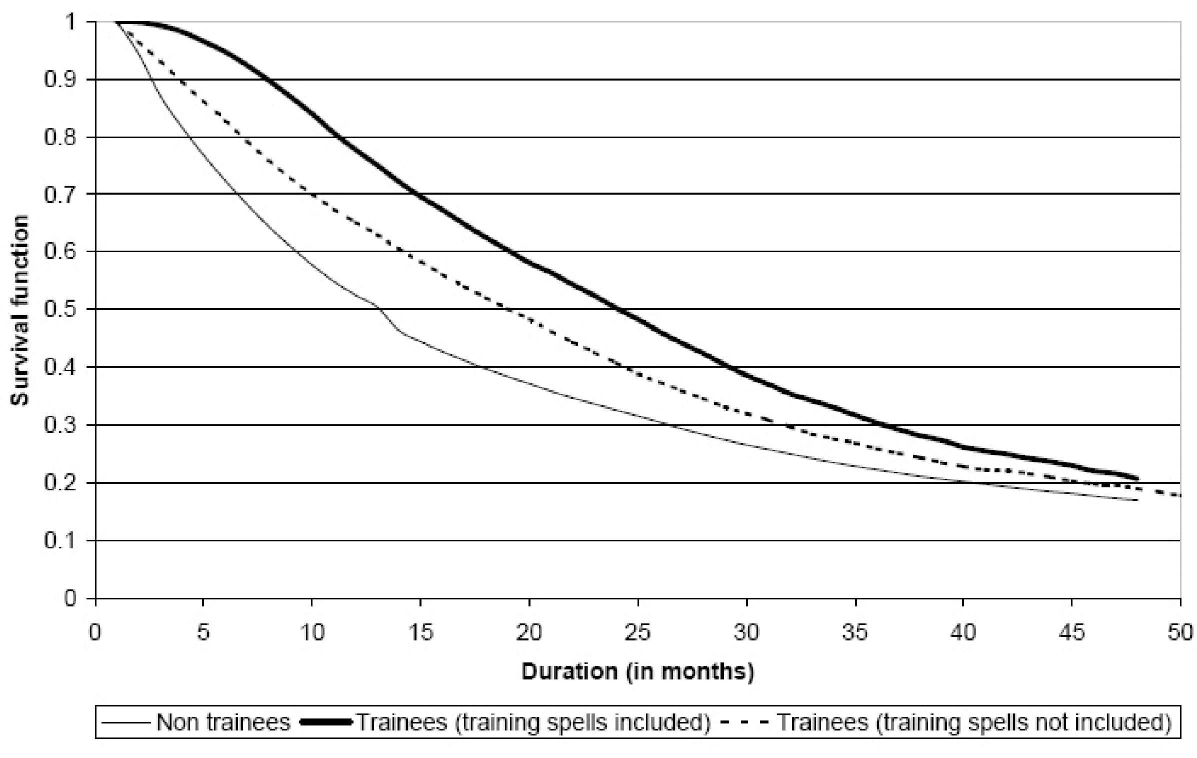

Figure 2: Kaplan-Meier estimates of survival functions of employment spell durations

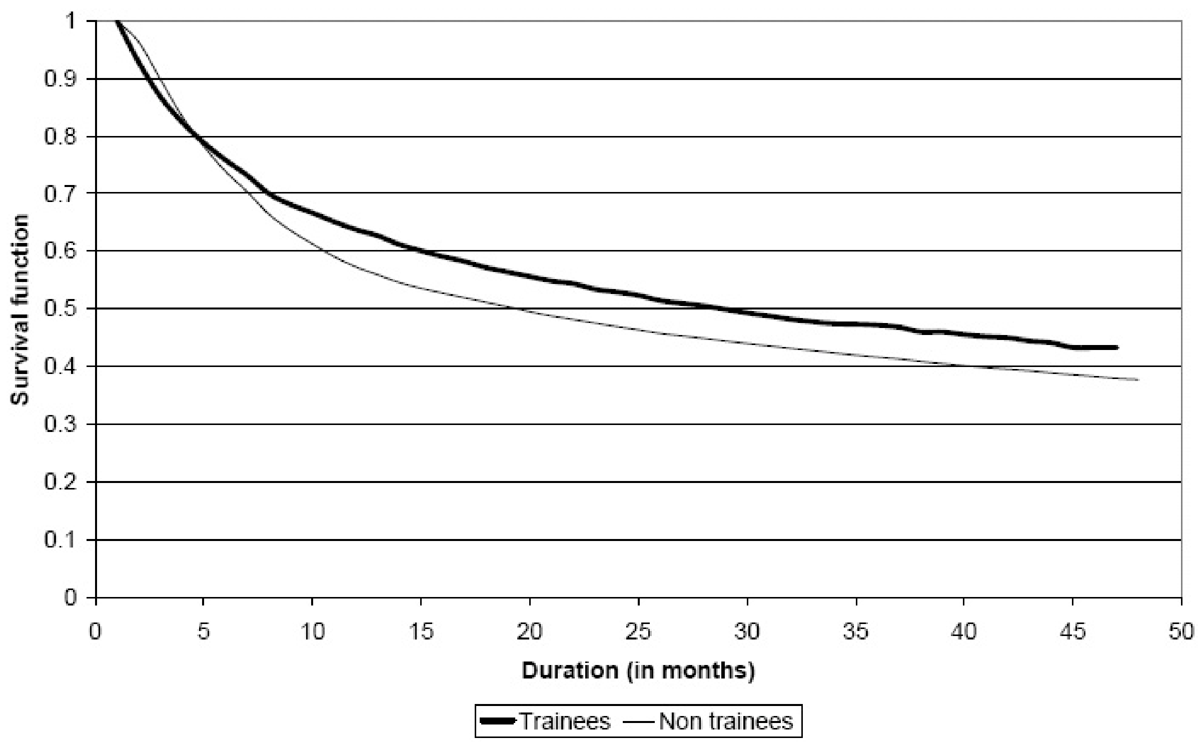

Figure 3: Nonparametric estimate of the transition rate from unemployment to training

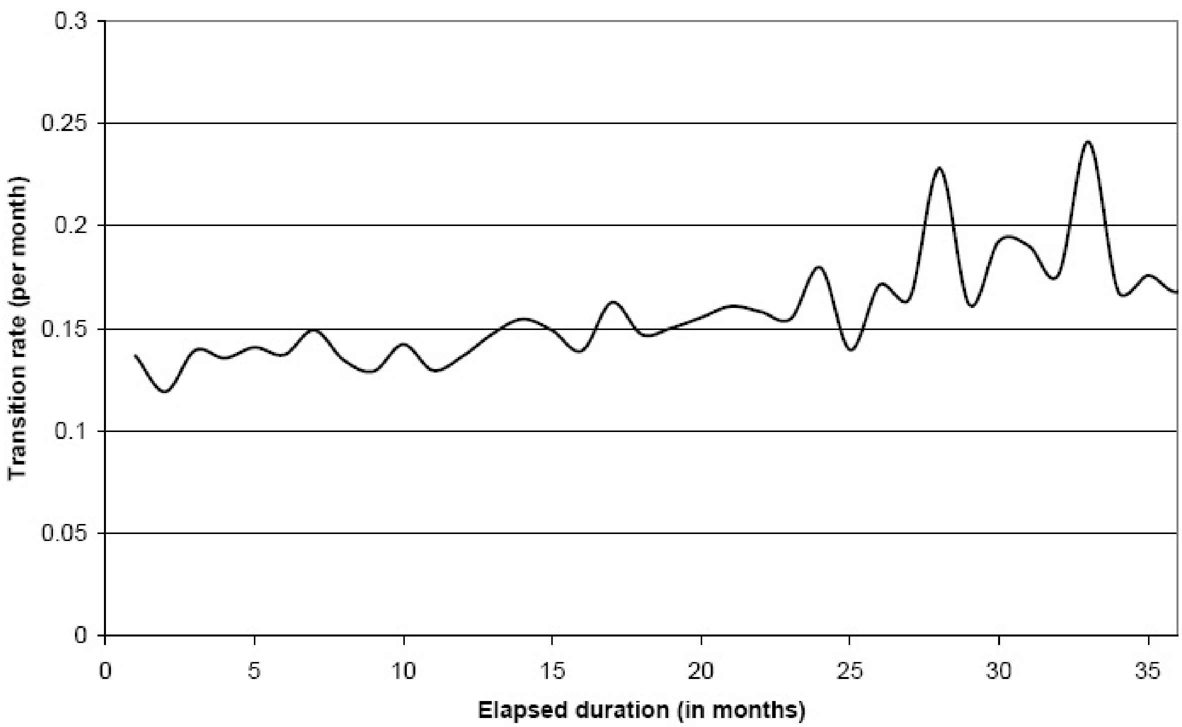

Table 1: Sample characteristics

	No training	Training
Male	53 %	50 %
Female	47 %	50 %
Primary and junior high-school	84 %	80 %
Upper secondary high-school	12 %	14 %
Post-secondary education	4 %	6 %
French	90 %	94 %
Foreigner	10 %	6 %
Age below 25	36 %	35 %
Age 25-35	34 %	37 %
Age 35-45	18 %	19 %
Age 45-55	12 %	9 %
Unemployment recurrence	43 %	36 %
No unemployment recurrence	57 %	64 %

Note. Source: FNA-UNEDIC, authors computations. 2001-2005, 270,139 spells

Table 2: Estimated values of the Vuong test statistics for the choice of the unobserved heterogeneity (UH) distribution

	without UH	binomial	normal	Beta
binomial	41.03	–	–	–
normal	11.78	-37.04	–	–
Beta	28.93	-25.92	20.25	–
mixture of normal distributions	29.14	-18.98	22.31	3.89

Note. Interpretation: The test statistics for the hypothesis that the binomial model is better than the model without UH is equal to 41.03.

Table 3: **Estimated parameters of the unemployment-employment transition rate**

Variables	**Parameter estimates**	**Std. err.**
Intercept	**-7.166**	0.062
Demographic variables		
Male	**0.174**	0.011
French nationality	0.018	0.014
18-26 years old	**0.235**	0.014
26-35 years old	**0.185**	0.006
35-45 years old	**0.272**	0.008
Employment history		
Previous wage	**-0.027**	0.006
Previous wage missing	**0.378**	0.057
Length of the previous period of contribution to UI	**-0.143**	0.050
No previous contribution to the UI system	**-0.116**	0.015
Unemployment benefits (in log euros)	**-0.094**	0.029
No unemployment benefits	**1.544**	0.049
Cumulated unemployment duration over the past 2 years (in log)	**0.029**	0.002
Number of previous unemployment spells over the past 2 years	**0.781**	0.012
Remaining duration of eligibility to UI (at the end of the unemployment spell)	**0.425**	0.011
Education and skills		
Secondary education	**0.290**	0.012
Post-secondary education	-0.019	0.017
Blue-collar	**0.042**	0.015
Executive	**0.056**	0.007
White-collar	**-0.053**	0.007
Skill unknown	**0.164**	0.012
Previous training		
Total time spent in training during the previous unemployment spells	**0.027**	0.008
No training in the previous unemployment spells	**0.016**	0.07
Last job		
Short-term contract	**0.041**	0.015
Size of the previous firm:		
Less than 10 employees	**-0.054**	0.012
From 10 to 50 employees	-0.020	0.023
From 50 to 100 employees	**0.120**	0.011
From 100 to 500 employees	**0.134**	0.010
More than 500 employees	**-0.030**	0.010
Local unemployment rate:		
Second quartile	**0.278**	0.007
Third quartile	**0.171**	0.012
Fourth quartile	**-1.427**	0.042

Source: FNA-UNEDIC, 2001-2005, 270,139 spells. In bold: significant at the 5% level.

Table 4: Estimated parameters of the unemployment-training transition rate

Variables	**Parameter estimates**	**Std. err.**
Intercept	**-9.784**	0.158
Demographic variables		
Male	**-0.331**	0.040
French nationality	0.042	0.033
18-26 years old	**0.491**	0.047
26-35 years old	**0.181**	0.017
35-45 years old	**0.160**	0.019
Employment history		
Previous wage	**0.266**	0.021
Previous wage missing	**-2.008**	0.185
Length of the previous period of contribution to UI	**-0.379**	0.116
No previous contribution to the UI system	-0.007	0.038
Unemployment benefits (in log euros)	0.119	0.067
No unemployment benefits	**-1.309**	0.362
Cumulated unemployment duration over the past 2 years (in log)	**-0.071**	0.005
Number of previous unemployment spells over the past 2 years	**0.932**	0.031
Remaining duration of eligibility to UI (at the end of the unemployment spell)	**0.663**	0.027
Education and skills		
Secondary education	**-0.501**	0.029
Post-secondary education	0.055	0.041
Blue-collar	0.036	0.034
Executive	0.001	0.019
White-collar	**-0.052**	0.018
Skill unknown	**-0.100**	0.026
Previous training		
Total time spent in training during the previous unemployment spells	0.020	0.020
No training in the previous unemployment spells	**0.073**	0.024
Last job		
Short-term contract	0.051	0.036
Size of the previous firm:		
Less than 10 employees	**0.066**	0.030
From 10 to 50 employees	0.055	0.054
From 50 to 100 employees	**0.377**	0.027
From 100 to 500 employees	**0.212**	0.025
More than 500 employees	**0.210**	0.025
Local unemployment rate:		
Second quartile	**0.148**	0.017
Third quartile	**0.356**	0.033
Fourth quartile	**1.195**	0.108

Source: FNA-UNEDIC, 2001-2005, 270,139 spells. In bold: significant at the 5% level.

Table 5: Estimated parameters of the training-unemployment transition rate

Variables	**Parameter estimates**	**Std. err.**
Intercept	**-3.789**	0.186
Demographic variables		
Male	**0.096**	0.048
French nationality	**-0.191**	0.032
18-26 years old	-0.063	0.056
26-35 years old	**0.044**	0.019
35-45 yeras old	**0.070**	0.019
Unemployment history		
Reference wage	**-0.070**	0.026
No reference wage	0.304	0.248
Length of the period of contribution to UI when employed	**-0.602**	0.107
No previous contribution to the UI system	-0.010	0.040
Unemployment benefits (in log euros)	-0.068	0.070
No unemployment benefits	0.772	0.452
Cumulated unemployment duration over the past 2 years (in log)	**0.029**	0.006
Number of previous unemployment spells over the past 2 years	**-0.574**	0.034
Remaining duration of eligibility to UI (at the end of the unemployment spell)	**-0.434**	0.029
Education and skills		
Secondary education	**-0.267**	0.031
Post-secondary education	-0.039	0.046
Blue-collar	**-0.172**	0.034
Executive	**-0.052**	0.020
White-collar	-0.002	0.020
Skill unknown	**-0.080**	0.028
Previous training		
Total time spent in training during the previous unemployment spells	0.023	0.021
No training in the previous unemployment spells	0.034	0.026
Last job		
Short-term contract	0.038	0.040
Size of the previous firm:		
Less than 10 employees	0.004	0.033
From 10 to 50 employees	-0.087	0.059
From 50 to 100 employees	**-0.109**	0.028
From 100 to 500 employees	**-0.106**	0.027
More than 500 employees	-0.018	0.027
Local unemployment rate:		
Second quartile	-0.003	0.018
Third quartile	-0.041	0.037
Fourth quartile	0.147	0.147

Source: FNA-UNEDIC, 2001-2005, 270,139 spells. In bold: significant at the 5% level.

Table 6: Estimated parameters of the employment-unemployment transition rate

Variables	**Parameter estimates**	**Std. err.**
Intercept	**-7.312**	0.081
Demographic variables		
Male	**-0.080**	0.013
French nationality	**-0.053**	0.018
18-26 years old	-0.017	0.016
26-35 years old	**-0.256**	0.007
35-45 years old	**-0.013**	0.011
Employment history		
Previous wage	**0.020**	0.008
Previous wage missing	**-0.064**	0.070
Length of the previous period of contribution to UI	-0.112	0.062
No previous contribution to the UI system	**-0.046**	0.018
Unemployment benefits (in log euros)	-0.024	0.035
No unemployment benefits	**0.246**	0.056
Cumulated unemployment duration over the past 2 years (in log)	**0.067**	0.002
Number of previous unemployment spells over the past 2 years	**0.046**	0.015
Remaining duration of eligibility to UI (at the end of the unemployment spell)	**-0.115**	0.014
Education and skills		
Secondary education	**0.250**	0.015
Post-secondary education	-0.027	0.021
Blue-collar	**-0.087**	0.021
Executive	**-0.064**	0.009
White-collar	**0.040**	0.009
Skill unknown	**0.218**	0.015
Previous training		
Total time spent in training during the previous unemployment spells	0.014	0.010
No training in the previous unemployment spells	0.002	0.013
Last job		
Short-term contract	0.021	0.019
Size of the previous firm:		
Less than 10 employees	**0.031**	0.015
From 10 to 50 employees	**0.055**	0.028
From 50 to 100 employees	**0.163**	0.014
From 100 to 500 employees	**0.181**	0.013
More than 500 employees	**0.155**	0.014
Local unemployment rate:		
Second quartile	**-0.125**	0.009
Third quartile	**0.107**	0.015
Fourth quartile	**0.656**	0.053

Source: FNA-UNEDIC, 2001-2005, 270,139 spells. In bold: significant at the 5% level.

Table 7: Effects of training on the unemployment-employment transition rate (according to the values of individual covariates)

	Distribution of unobserved heterogeneity (UH)				
Variable	Without UH	**Binomial**	Normal	Mixed normal	Beta
Intercept	0.507	**0.020**	0.208	-0.138	-0.012
	(0.051)	(**0.066**)	(0.056)	(0.057)	(0.058)
Male	-0.043	**0.062**	-0.008	-0.005	0.012
	(0.023)	(**0.029**)	(0.025)	(0.025)	(0.026)
Less than 25 years old	-0.025	**0.189**	0.028	0.021	0.072
	(0.025)	(**0.032**)	(0.027)	(0.027)	(0.028)
Primary or junior high-school	0.061	**0.103**	0.071	0.076	0.067
	(0.048)	(**0.061**)	(0.052)	(0.053)	(0.053)
Days before benefit exhaustion (log)	0.100	**0.125**	0.119	0.120	0.112
	(0.023)	(**0.028**)	(0.024)	(0.024)	(0.025)
Unemployment recurrence (1)	-0.109	**−0.062**	-0.107	-0.116	-0.098
	(0.016)	(**0.022**)	(0.018)	(0.019)	(0.019)
6 to 12 months after the end of training	-0.393	**−0.157**	-0.346	-0.424	-0.285
	(0.031)	(**0.032**)	(0.031)	(0.032)	(0.032)
12 months and after the end of training	-0.396	**−0.017**	-0.319	-0.469	-0.190
	(0.033)	(**0.038**)	(0.034)	(0.036)	(0.035)
Training spells between 4 and 8 months	0.155	**−0.294**	-0.004	-0.086	-0.074
	(0.027)	(**0.036**)	(0.031)	(0.031)	(0.032)
Training spells between 8 and 12 months	0.368	**−0.415**	0.051	-0.090	-0.081
	(0.032)	(**0.042**)	(0.037)	(0.037)	(0.038)
Training spells longer than 12 months	0.686	**−0.480**	0.178	-0.048	-0.035
	(0.063)	(**0.075**)	(0.070)	(0.072)	(0.072)
Mean log-likelihood	-7.0572	**−7.0403**	-7.0533	-7.0449	-7.0462

Standard errors are reported between parentheses. In bold : results for the best specification
(1) Number of unemployment spells over the past two years

Table 8: Effects of training on the employment-unemployment transition rate (according to the values of individual covariates)

	Distribution of unobserved heterogeneity (UH)				
Variable	Without UH	**Binomial**	Normal	Mixed normal	Beta
Intercept	-0.026	$\mathbf{-0.248}$	-0.105	-0.192	-0.193
	(0.081)	(**0.084**)	(0.082)	(0.081)	(0.083)
Male	0.031	**0.088**	0.049	0.051	0.057
	(0.040)	**(0.041)**	(0.041)	(0.041)	(0.041)
Less than 25 years old	-0.058	$\mathbf{-0.009}$	-0.047	-0.058	-0.034
	(0.042)	(**0.043**)	(0.042)	(0.042)	(0.043)
Primary or junior high-school	-0.016	$\mathbf{-0.009}$	-0.019	-0.011	-0.021
	(0.078)	(**0.080**)	(0.079)	(0.079)	(0.079)
Days before benefit exhaustion (log)	-0.090	$\mathbf{-0.089}$	-0.085	-0.088	-0.088
	(0.037)	(**0.037**)	(0.037)	(0.037)	(0.037)
Unemployment recurrence (1)	-0.112	$\mathbf{-0.095}$	-0.110	-0.118	-0.113
	(0.027)	(**0.028**)	(0.028)	(0.028)	(0.028)
Training spells between 4 and 8 months	0.001	$\mathbf{-0.116}$	-0.054	-0.056	-0.085
	(0.048)	(**0.049**)	(0.048)	(0.048)	(0.049)
Training spells between 8 and 12 months	-0.108	$\mathbf{-0.335}$	-0.225	-0.230	-0.284
	(0.060)	(**0.061**)	(0.061)	(0.061)	(0.061)
Training spells longer than 12 months	-0.151	$\mathbf{-0.481}$	-0.337	-0.353	-0.439
	(0.125)	(**0.125**)	(0.126)	(0.125)	(0.126)
Mean log-likelihood	-7.0572	$\mathbf{-7.0403}$	-7.0533	-7.0449	-7.0462

Standard errors are reported between parentheses. In bold : results for the best specification
(1) Number of unemployment spells over the past two years

Table 9: Simulated net effects of training (in days)

	Remaining unemployment duration *				
Distribution of unobserved heterogeneity (UH)	Mixed normal	Without UH	**Binomial**	Normal	Beta
All training spells	+102	+20	**+93**	+87	+108
	Employment duration				
Distribution of unobserved heterogeneity (UH)	Mixture	Without UH	**Binomial**	Normal	Beta
All training spells	+335	+135	**+336**	+286	+305
Early training (start before 90 days of unemployment)	+385	+144	**+376**	+263	+360
Late training (start after 180 days of unemployment)	+285	+123	**+313**	+208	+252

*From the beginning of the training spell. In bold : results for the best specification.