The Effects of On-the-job and Out-of-Employment Training Programmes on Labor Market Histories†

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Abstract. We evaluate the impact of both on-the-job and out-of-employment training programmes on the mobilities on the labour market. Using French data giving individual work histories over five years, we estimate a multi-spell multi-state transition model with unobserved heterogeneity to take participation in programmes and their duration as endogenous and to study both current and past duration and state dependencies. Training has a lasting effect on the individual trajectories and there are interdependencies between the two types of training. On-the-job training increases the risk of separation, but it increases, like out-of-employment training, the hazard rate to employment.

Keywords: Training, Transition Models, Panel Data, Unobserved Heterogeneity.

JEL Classification: J64, C41, C10, J69.

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1 Introduction

Training schemes offered to the unemployed workers and public incentives given to promote firm-provided training have been largely developed in Europe over the past decades. Designed to remedy against the inequalities from schooling and to promote the lifelong acquisition of new abilities and qualifications, continuous training is considered as a key vector for social and professional promotion. With greater labour market flexibility, it appears crucial to give the workers the means to adapt to an evolving and uncertain labour market. Continuous training is thus an important component in the flexicurity reforms promoted by the European Union. In France in particular, a number of reforms have been implemented in the 2000s to give the worker a greater role to play in this way through the training system and to encourage firms to train their employees, even if the content of the training desired by the employee is not directly related to the firm's activity. These reforms promoting the accumulation of general human capital and reconversions are implemented with the expectation that it would ease mobilities on the labour market and improve the employment prospects of the participants. However the existing econometric evaluations of training do not always support such an assumption (see Heckman *et al.*, 1999 and Bassanini *et al.*, 2005 for a survey). In this paper, we offer to evaluate whether on-the-job and out-of-employment training programmes help the workers to keep a greater attachment to the labour market, reducing non employment occurrence and duration on the one hand, and increasing reemployment and employment stability on the other.

It is important to evaluate jointly the impact of on-the-job and out-of-employment training programmes on labour market transitions in the mid and long runs. Still, the literature evaluates the two types of programmes separately and the empirical evidence for the mid-run effects of on-the-job training is scarce. The literature on training schemes offered by the public employment services to unemployed workers focuses on unemployment duration and reemployment stability (see for example the recent studies Bergemann *et al.*, 2009, Fitzenberger *et al.*, 2010, Lechner *et al.*, 2011 and Crépon *et al.*, 2012). It shows no univocal effects on the labour market transition processes : the lock in effect tends to increase the unemployment duration, leading to negative short-term effects, but the accumulation of human capital would increase the reemployment duration (Crépon *et al.*, 2012), giving positive returns in the longer run (Lechner *et al.*, 2011). Empirical studies on firm-provided training rather consider job stability, wages or productivity effects (see for example Picchio and van Ours, 2011 and Dearden *et al.*, 2006), but offer less evidence about future unemployment outcomes. With this respect, they show that these schemes have strong positive employment effect (Picchio and van Ours, 2011), especially for young workers and women (Gritz, 1993).

We estimate a multi-spell multi-state transitions models using a French survey (2003 FQP survey, INSEE) that gives, for a sample individuals representative of the French labour force, detailed information on labour market history and on participation in all kind of training programmes over a five-year period. This approach presents several advantages. First, we do not focus on a specific population and type of programme in order to gain more generality in our evaluation. In line with the literature, we nevertheless account for the inherent differences existing between programmes offered to unemployed workers and those provided to employed workers, by allowing the processes of access and the effects of these two programmes to be different. Second, our econometric model explicitly takes as endogenous participation in training programs and its duration to account for selection on observable and unobservable characteristics (Bassanini *et al.*, 2005]; OECD, 2003). To treat the selection problem and identify the effects of participation in training programmes on the conditional non employment and employment duration distributions, we model all the transitions and allow for correlations between the state-specific unobserved components. As we model unobserved heterogeneity and initial conditions *à la* Wooldridge, 2005, we distinguish true and spurious dependencies. Third, we allow participation to have an impact on the labour market transitions up to 12 months after entry into the program. We thus consider both current and lagged state dependencies, as well as current and lagged duration dependencies (Heckman and Borjas, 1980), explicitly accounting for potential time-varying effects of training. All in all, this empirical model allows us to evaluate how the continuous training system as a whole affects the labour market transition process of participants. We can evaluate how the amount of on-the-job training affects the distribution of the employment duration, but also the duration out of employment and reemployment duration. We can also test whether there exists some interaction between training on- and out-the job.

Overall our results are rather positive concerning the impact of participation in training programmes on the degree of attachment to the labour market in the medium run, running along with the existing literature. We find that both types of training increase the probability of reemployment for workers out-of-employment, and that participating in a training programme during a non employment spell increases reemployment stability. If we observe that on-the-job training increases the instantaneous risk of non employment, the hazard to reemployment is higher for non employed workers who participated in a training programme while employed in the previous year. This runs in line with the idea that training increases mobilities and that previous participation in training is valued by prospective firms. Moreover it reveals the social returns to on-the-job training, and contributes to the literature showing the necessity of not limiting the evaluation of training schemes to short term outcomes.

This paper is organized as follow. Section 2 describe the data . We present the empirical model and the estimation method in Section 3. In Section 4 we discuss the results and in Section 5 we perform simulation exercises. Section 6 concludes.

2 The data

2.1 The data

We use the French survey *Formation et Qualification Professionnelles* (FQP hereafter) collected in 2003 by the French national institute (INSEE). These data are nationally representative of the French population aged between 17 and 65 years old. They provide retrospective calendars which depict, on a monthly basis, the situation of the individual on the labour market from May 1998 to May 2003. As a result, we have a 60 months follow-up for each interviewed individual.

The professional calendar allows to retrieve the detailed work history of individuals. It lists all the transitions from/to unemployment or inactivity, but also all the job-to-job transitions the individual experiences during the period of observation. A new period in the calendar is indeed motivated by a transition from/to non employment, but also by a change in the characteristics of the employment situation (change in contract, firm, establishment or position). Transitions between unemployment and inactivity are however not reported in the calendar[1]. We have a rich information on the characteristics of the employment spell, among which the dates of beginning and end, the precise motivations for the end of a spell of employment (resignation, lay off, end of the term of the contract) and the type of contract (short, temporary or permanent). The wage associated with each job or the characteristics of the firms are however not available for intermediate

[1] We know whether the individual enters unemployment or leaves the labour force when the job ends, but we do not know if he stayed in the same state until his next employment spell.

spells[2].

The survey also gives information on participation in training programs exceeding 30 hours for the period going from 1998 to 2003. Several categories of training can be distinguished, such as training on employment, internship, training out of employment and apprenticeship. We know the effective duration and length of each training listed in the calendar, and it is possible to determine the category and the main characteristics for the great majority of them. Table 1 gives a brief description of the considered training.

[TABLE 1]

2.2 Sample selection

As we aim at, among others, evaluating the impact of training on the risk and duration out of employment, we select a sample composed by individuals aged between 17 and 64 years old, who have finished school before May 1998 and do not go back to school, are not retired on May 2003 and who are not civil servant, nor self-employed[3]. This selection is made to rule out the possibility of transition from/to school and retirement to clarify the definition of the state "non employment", which gathers both unemployment and inactivity. Indeed, these kinds of inactivity are very specific and are not at the center of our interest. We do not consider the observations corresponding to civil servant and self-employed because their labour market transition processes are specific. We obtain a sample of 26007 individuals. Table 2 gives the main characteristics of our sample. As shown in table 1, between 1998 and 2003 there where 7437 training programmes lasting more than 30 hours, 82% of which occurred during an employment spell. Training periods out of employment last longer than training periods during employment, with on average 5 months versus 2,6 months.

[TABLE 2]

2.3 Descriptive analysis

We consider 4 states: employment, non employment, employment training and out-of-employment training. We classify training as an employment training or an out-of-employment training depending on the state held at the moment of the training period. We aggregate the unemployment

[2]We only know whether remuneration stagnates, decreases or increases with the transition.

[3]But we keep non civil servant employed by the State.

and out-of-labour-force spells in a "non employment" state because the data do not allow to distinguish the transitions between unemployment and non participation. We consider employment as an aggregate spell, without taking into account the job to job transitions, to keep the model of trajectories tractable : if an individual holds for example 5 different jobs without experiencing any transition to non employment, then we assume that he occupies only one state. As a consequence, we evaluate the impact of training on the persistence of employment. A further research could consist in allowing for the transitions from job to job, in order to investigate the issue of inter versus intra firms mobilities.

As the calendar is filled on a monthly basis, we encounter an interval-censoring issue. This can be corrected using an appropriate specification of the transition probabilities (see section 3). The main issue involved by this interval-censoring is that very short spells - which duration is beyond one or two weeks - may not be listed. This may explain why we observe in the data some unusual transitions. For example, 132 individuals are observed making a transition from employment to non employment training. It is unlikely that these workers entered non employment training the very first day of their non employment spell. Such observed transitions may rather stand for a transition from employment to non employment and then a transition from non employment to training within the same month. When it is possible, we have corrected these observations to reveal the actual trajectories. We thus imposed some constraints on the transitions, but only 0.06% of the transitions are modified. The constrained transition matrix (Table 3) is quite similar to the unconstrained one. The following econometric analysis is applied to the data summarized by this transition matrix below.

[TABLE 3]

As expected, the transition matrix exhibits strong inertia. The probability of exiting the occupied state the following month is however greater when the individual is in a training program. The monthly probability of entering in an on employment (resp. non employment) training program is quite low, accounting for about 0,6% (resp. 0.3%), given that the individual occupies a job (resp. is unemployed). 15,2% of the unemployed workers who participate in a non employment training program a given month return to non employment the following month. 19,7% of the employed workers who are in training go back to employment the following month.

We first run Kaplan-Meier estimates of the survival function of the durations of employment and non employment (Appendix A). We assume here that training participation is exogenous[4]. We stratify the estimates according to the participation or not in a training during the spell (Figure A1)[5]. To shed light on the existence of past dependencies, we also stratify the Kaplan-Meier estimates according to past participation in training programs (Figure A2). The tests always reject the null hypothesis of homogeneity of the strata. Employment and non employment spells with participation in training last longer than the others. The individuals who previously participated in training programs have shorter employment spells in the future. The non employment spells following a participation in a training program are shorter than the others.

Causal interpretation is impossible at this stage of the analysis as the Kaplan-Meier estimates capture both the causal and selection effects. Nevertheless, according to this preliminary analysis, training participation and current spell duration are positively correlated, while past training participation and future spell durations are negatively correlated. In the following, we use the panel structure of our data to correct for the selection bias and identify the causal effect of training on the transitions on the labour market.

3 Modeling transitions

3.1 Labour market participation process

To evaluate the effect of participation in training programmes on the trajectory on the labour market, we consider a discrete-time discrete-state labour market participation process (see, for instance, Fougère and Kamionka, 2008; Heckman, 1981; Lancaster, 1990): the labour market history of a given individual can be represented by a sequence of realizations of a discrete time stochastic process Y_t,[6] $t \in \{1, \ldots, 60\}$, taking its value in a discrete-state space $E = \{1, 2, 3, 4\}$.Y_t is the state occupied by the individual during the month t. The realizations of the process are in-

[4]This assumption is relaxed later on.

[5]We also stratify the Kaplan-Meier estimates depending on the kind of training. The graphs, not displayed in the appendix, are very similar to the ones we show

[6]We omit the index of the individuals.

dependent and identically distributed. Let $\{y_t, 1{\leq}t{\leq}60\}$ be a realization of the process.

$$y_t = \begin{cases} 1, & \text{if the individual is employed at time } t, \\ \\ 2, & \text{if the individual is non employed at time } t, \\ \\ 3, & \text{if the individual is on employment training at time } t, \\ \\ 4, & \text{if the individual is on out-of-employment training at time } t, \end{cases}$$

where $t \in \{1, \ldots, 60\}$.

We do not distinguish between inter- and intra-firm mobility, nor consider job stability/mobility, but evaluate the impact of training on the access to employment and the stability of the employment sequence. Although extending the analysis at the job level would be of high interest, the lack of precise information about the content and degree of generality or specificity of training makes such an analysis difficult and would make the model much more complex. Moreover, our first interest is to evaluate whether training is effective to put people back to work and to protect them against non employment. With this respect, the transition process between employment and non employment and the distribution of durations of the periods in- and out-of-employment are highly informative. Elsewhere, the data do not give information about wages, so that we cannot evaluate the impact of training on this dimension. But this effect has been largely documented in the literature (Parent, 1999 and Parent, 2003; Blundell *et al.*, 1999, Pischke, 2001; Gerfin, 2003; Goux and Maurin, 2000; Fougère *et al.*, 2001).

To consider past dependencies, we assume that training plays a role in the transition probabilities up to 12 months after entry into the programme. This amounts to assuming that the human capital acquired in a training depreciates over time and is lost after a year. Therefore we assume that the knowledge learned in a training period may only have mid-term effect on the productivity or employability, any longer-run differences observed between trained and not trained individuals being due to learning-by-doing. Since conditioning on the exact sequence of realizations of Y_t in the previous year would be too data-consuming, we capture previous work history using the amount of months the individual spent in each and other considered states in the previous year. We nevertheless allow for a time-heterogeneous effect by decomposing the previous year into two periods. We thus assume that the monthly transition probabilities at time t

depend on the abstracts $\phi_{t-1} = (\phi^k_{t-1,t-6}, \phi^k_{t-12,t-6})'$, with $\phi^k_{t-1,t-6} = \sum_{s=1}^{6} \mathbb{I}[y_{t-s} = k]$ and $\phi^k_{t-12,t-6} = \sum_{s=7}^{12} \mathbb{I}[y_{t-k} = k]$, for $k = 1, 2, 3, 4$.

We assume that conditional on the characteristics of the individual (z, ν), on the previous state occupied by the individual y_{t-1} and given the most recent realization of the component ϕ_{t-1}, the state occupied by the individual at time t is independent from older history of the process y_{t-j}, where $j \geq 2$. Consequently, for months $t = 13, \ldots, 60$, $j \in \mathbb{N}$ and $j \geq 2$,

$$Y_t \perp\!\!\!\perp Y_{t-j} \mid y_{t-1}, \phi_{t-1}, \phi_{12}, x, \nu.$$

The conditioning on ϕ_{12} and the fact that we model transitions from the 13th month come from our treatment of the initial conditions problem, as explained in the following section.

3.2 Initial Conditions

The initial time $t = 1$ does not correspond to the date of entry into the labour market for all the individuals in the sample. At the beginning of the period of observation, individuals are not all localized at the same point in their transition process. The beginning of this process, from the end of schooling up to the state occupied on May 1998, is unobserved. In this paper the initial conditions are treated using the method proposed by Wooldridge, 2005[7]. The approach proposed by Wooldridge, 2005 conduces to add the initial conditions to the list of explanatory variables in the expression of the conditional transition probabilities given observed and unobserved heterogeneity and to specify the unconditional distribution of unobserved factors.

We assume that conditionally on the observed characteristics of the individual (x) and given the amount of time spent in each state of the labour market during the initial year, ϕ^2_{12}, ϕ^3_{12} and ϕ^4_{12}, the unobserved heterogeneity component V is independent from the state occupied by the individual a particular month of the beginning year. With V the unobserved heterogeneity vector, we have for $j = 1, \ldots, 12$,

$$V \perp\!\!\!\perp Y_j \mid \phi^2_{12}, \phi^3_{12}, \phi^4_{12}, x.$$

[7] Edon and Kamionka, 2007, show that in the case of a dynamic probit model the method proposed by Heckman, 1981 and the one proposed by Wooldridge, 2005 produce similar results.

The conditional contribution to the likelihood is then

$$\ell_\nu(\theta) = \prod_{t=13}^{60} \prod_{j=1}^{4} \prod_{k \in E_j} P(Y_t{=}k \mid y_{t-1}{=}j, \phi_{t-1}, \phi_{12}, x, \nu; \theta)^{\delta_{jkt}}, \tag{1}$$

where

$$\delta_{jkt} = \begin{cases} 1, \text{ if } y_{t-1} = j \text{ and } y_t = k, \\ \\ 0, \text{ otherwise.} \end{cases}$$

and $E_j \subset E$ is a subset of states (all transitions are not possible, see section 2). For instance, if the individual occupies state 1 (employment state), she/he can leaves this state to occupy state 2 (non employment) or state 3 (employment training). Consequently, $E_1 = \{2, 3\}$[8].

3.3 Specification and estimation

3.3.1 Transition probabilities

We specify the transition probabilities using a model directly related to mixed proportional hazard duration model in order to interpret straightforwardly the results[9].

In the expression (1) of the conditional contribution to the likelihood function, we have to specify the transition probability to occupy state k, $k \in E$, given the past history of the process $y_{t-1} = j$, ϕ_{t-1} and ϕ_{12}. We write this conditional probability as $p_{jkt}(\phi_{t-1}, \phi_{12}, x, \nu; \theta) = P(Y_t{=}k \mid y_{t-1}{=}j, \phi_{t-1}, \phi_{12}, x, \nu; \theta)$.

We assume that the conditional transition probabilities is

$$p_{jkt}(\phi_{t-1}, \phi_{12}, x, \nu; \theta) = \begin{cases} \dfrac{\psi_{jkt}}{\sum\limits_{k' \in E_j} \psi_{jk't}} \left(1 - \exp\left(-\sum\limits_{k' \in E_j} \psi_{jk't}\right)\right), \text{ if } k \neq j, \\ \\ \exp(-\sum\limits_{k' \in E_j} \psi_{jk't}), \text{ if } k = j, \end{cases} \tag{2}$$

where $\psi_{jkt} = \exp(X'_{jkt}\, a_{jk} + \phi'_{t-1} b_{jk} + v_{jk}) = \exp(X'_{jkt}\, a_{jk} + \phi'_{t-1} b_{jk} + \lambda_{jk}\, \nu_1 + \mu_{jk}\, \nu_2 + \phi'_{12}\gamma_{jk})$. X_{jk} is a vector of exogenous variables specific to the transition from state j to state k, $k \in E_j$ and $j \in E$. $a_{jk} \in I\!R^p$, $b_{jk}, \gamma_{jk} \in I\!R^3$ are vector of parameters.

[8] Let us assume that $E_2 = \{1, 4\}$, $E_3 = \{1\}$ and $E_4 = \{2\}$. Finally, a total of 6 transitions between distinct states are examined.

[9] To evaluate the impact of the training on the current state duration, we could consider training as a sub-spell of the employment or non employment spell (Crépon *et al.*, 2012), and not as a separate state as it is commonly defined. Combined with interval-censoring, this requirement makes the implementation of a timing-of-events approach (see **?**) untractable, even if we postulate constant hazards.

There is a direct relation between this specification of the transition probabilities and the econometrics of multi-spell multi-state models (see Flinn and Heckman, 1983, Fougère and Kamionka, 2008). Indeed, $\exp(-\sum_{k'\in E_j} \psi_{jk't} \times 1)$ represents the conditional probability to stay in state j one month again (or to 'survive' in this state). The expression $1 - \exp\left(-\sum_{k'\in E_j} \psi_{jk't} \times 1\right)$ represents[10] the conditional probability to stay in state j exactly one month more. Given the individual leaves the state j, the expression $\psi_{jkt}/(\sum_{k'\in E_j} \psi_{jk't})$ is the conditional probability to enter into state k, $k \in E_j$. Finally, ψ_{jkt} can be interpreted as a conditional hazard function for the transition from state j to state k.

3.3.2 Unobserved heterogeneity

We use a factor loading model in order to correlate in a flexible way transitions probabilities using unobserved heterogeneity.

Let v_{jk} denote the unobserved heterogeneity term specific to transition from state j to state k $(j, k \in E)$. Assume that

$$v_{jk} = \lambda_{jk}\, \nu_1 + \mu_{jk}\, \nu_2,$$

where ν_1 and ν_2 are two unobserved random components $(\nu = (\nu_1, \nu_2)')$. $\lambda_{jk}, \mu_{jk} \in I\!R$ are parameters. For identification, μ_{13} is fixed to 0.

We have considered two specifications for the distribution of the unobserved heterogeneity vector $V = (V_1, V_2)'$: a discrete distribution and a normal distribution with two independent factors.

A discrete distribution Let us assume that $\nu_j \in \{-1; 1\}$, for all $c = 1, 2$. The joint distribution of $\nu = (\nu_1, \nu_2)'$ is discrete. We assume that

$$\text{Prob}[V = (\nu_1^0, \nu_2^0)'] = \begin{cases} \pi_{00}, & \text{if } \nu_1^0 = -1 \text{ and } \nu_2^0 = -1, \\ \pi_{01}, & \text{if } \nu_1^0 = -1 \text{ and } \nu_2^0 = 1, \\ \pi_{10}, & \text{if } \nu_1^0 = 1 \text{ and } \nu_2^0 = -1, \\ \pi_{11}, & \text{if } \nu_1^0 = 1 \text{ and } \nu_2^0 = 1, \end{cases}$$

[10]Let $S_{jt} = \sum_{k'\in E_j} \psi_{jk't}$. Then Prob$[0 \le U \le 1 \mid S_{jt}] = \int_0^1 S_{jt}\ \exp(-S_{jt}\ u)\, du = 1 - \exp(-S_{jt}\ u)$. It is the conditional probability that the individual stay at most 1 units of time more in state j. We assume that, at most, one transition can occur within a given month. U represents the forward duration in state j. The conditional distribution of this forward duration is an exponential distribution.

where $0 \leq \pi_{cc'} \leq 1$ and $\sum_{c=0}^{1} \sum_{c=0}^{1} \pi_{cc'} = 1$.

The conditional contribution to the likelihood function is

$$\ell(\theta) = \sum_{c=0,1} \sum_{cc'=0,1} \ell_{(2c-1,2cc'-1)}(\theta)\, \pi_{jk}. \tag{3}$$

Here, we have three additional parameters to estimate: π_{00}, π_{01} and π_{10}.

This approach is similar to the one proposed by Heckman and Singer, 1984. The number of points of the mixture is fixed to 4. This approach is often used for the estimation of transition model (see Gilbert *et al.*, 2011).

In practice, in order to estimate the model, we use the following parametrization of the distribution of the unobserved heterogeneity component

$$\pi_{cc'} = \frac{\exp(c_{cc'})}{\sum_{a=0}^{1} \sum_{b=0}^{1} \exp(c_{ab'})},$$

where $c_{cc'} \in \mathbb{R}$, $c, c' \in \{0, 1\}$, are parameters ($c_{11} = 0$).

When the unobserved heterogeneity factors V_j, $j = 1, 2$, are discrete, the likelihood function can be maximized directly with respect to the parameters.

A continuous distribution V_1 and V_2 are assumed independent and identically distributed. V_1 and V_2 are distributed as a standard normal distribution. In this case the unobserved term space is $\Omega = \mathbb{R}^2$ and the conditional contribution to the likelihood function is

$$\ell(\theta) = \int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} \ell_{\nu}(\theta)\, \frac{1}{2\pi} \exp(-0.5\,(\nu_1^2 + \nu_2^2))\, d\nu_1\, d\nu_2 \tag{4}$$

where $\nu = (\nu_1, \nu_2)'$.

We propose to maximize the simulated likelihood (SML) obtained replacing each contribution (**??**) by the expression

$$\hat{\ell}(\theta) = \frac{1}{H} \sum_{h=1}^{H} \prod_{t=13}^{60} \prod_{j=1}^{4} \prod_{k \in E_j} p_{jkt}(\phi_{t-1}, \phi_{12}, x, \nu_h; \theta)^{\delta_{jkt}},$$

where the drawings ν_h, $h = 1, \ldots, H$, are i.i.d. $N(0, 1)$ and specific to the individual.

The SML estimator $\hat{\theta}_{HN}$ is asymptotically efficient (see, Gouriéroux and Monfort, 1991). If

$\frac{N}{H} \longrightarrow 0$, then $\sqrt{n}(\hat{\theta}_{NH} - \theta_0) \longrightarrow N(0, I(\theta_0)^{-1})$, where $I(\theta) = E[\frac{\partial \ln(\ell_i(\theta))}{\partial \theta} \frac{\partial \ln(\ell_i(\theta))}{\partial \theta'}]$ and $\ell_i(\theta)$ is the contribution of individual i to the likelihood function, $i = 1, \ldots, N$. In practice, a limited number of drawings allows to obtain a good approximation for the true value of the parameters (see, Kamionka, 1998, Kamionka and Lacroix, 2010, Laroque and Salanié, 1993).

4 Evaluation of the impact of training

Results are shown in Appendix B. For each transition, we have three set of parameters. In the first column ((1a) or (2a)), are given the results when we omit unobserved heterogeneity ; in the second column ((1b) or (2b)), there are the results we get when we use a discrete distribution for the unobserved heterogeneity ; and in the third column ((1c) or (2c)), we report the results of the model with a continuous distribution for the unobserved heterogeneity.

4.1 Conditional probabilities to enter into training

The monthly probability of entering a training programme, either on-the-job or not, increases with the level of education, even if education has a stronger effect on access to training for employed than non employed (Table B3). Younger workers have a greater monthly probability of entering a training programme. Workers aged over 46 year-old, and in particular over 55 year-old, have the lowest probability of accessing training, which is a well-documented result. Finally, women and foreigners have a lower monthly probability of entering a programme than men and French respectively. The effect of nationality is the most detrimental for the access to on-the-job training than for the access to out-of-employment training.

Concerning past state dependencies, we find non linear effects and selection on unobservables for both kinds of training programmes. Overall, the more an employed worker experienced non employment periods in the previous year, the higher her/his monthly probability of entering an employment training programme. When we look at the timing, we observe that more recent periods of non employment has a negative effect on on-the-job training probability, while older periods of non employment has a positive effect on on-the-job training probability. This indicates that access to this kind of training has a non linear effect with employment duration. For an individual who is not employed, the monthly probability of entering out-of-employment training increases with the time spent on employment during the previous year. This would indicate that the greater the attachment to employment, the greater the probability of being trained when not employed. Accounting for unobserved heterogeneity reduces this positive relationship between past employment and out-of-the-job training participation. The probability of participating in an employment training programme increases (respectively decreases) with the share of time spent on employment training (respectively non employment training) in the 6 previous months, indicating participation recurrence. There are however time-varying effects: the more an employed worker participated in an out-of-employment training programme in the first part of the previous year, the greater his monthly probability of entering employment training, but more recent participation in out-of-employment training has an opposite effect on employment training participation. The monthly probability of entering an out-of-employment training period when not employed increases with more recent participation in out-of-employment training and with more old participation in employment training. There is selection on unobservables. When we account for unobserved heterogeneity, the recurrence effect of employment training on employment training participation increases in absolute value, but remain significant. The effect of both previous employment and out-of-employment training participation on participation in out-of-employment training decreases in absolute value when we take into account the presence of unobserved heterogeneity. On the contrary, accounting for unobserved heterogeneity reinforce the effect of past participation in out-of-employment training on employment training participation. We can interpret this result as follows: previous participation in programs may reveal the willingness of the employee (or not employed worker) to participate in such programs and his ability to benefit from it, so that the employer (or the public service of employment) is more likely to offer training to an individual who has already been trained than to others.

4.2 Duration of training

Gender does not significantly affect the duration of out-of-employment training, but it does affect the duration of employment training, women participating in longer employment training than men (Table B2). Education and nationality appear to have a insignificant or small impact on training duration. Lastly, workers younger than 26 and older than 55 participate in longer employment training programmes. Longer out-of-employment training spells are experienced by workers over 55.

We observe mid-run past state dependencies in the monthly probability of exiting employment training: the parameters associated with the recent past are globally insignificant, while those associated with the older past are significant. On the contrary, recent past is more determinant for the duration of out-of-employment training. The situation on the labour market in the previous year only matters for the duration of employment training: the more the worker spent an important share of the first part of the previous year out-of-employment, the longer the employment programme. This has however no effect on the duration of the out-of-employment training programme. The time previously spent in out-of-employment training reduces the length of the employment training period. It however lengthens the duration of out-of-employment training, indicating negative duration dependence of out-of-employment training. The time previously spent in employment training increases the duration of the current employment training participation, but shortens the current out-of-employment training participation.

4.3 Impact of training on the risk of separation and on employment duration

We now look at the determinants of the monthly probability of exiting employment, that is on the employment stability (Table B1). The socio-demographic characteristics have the expected effect: the instantaneous probability of exiting employment to non employment decreases with the level of education. It is greater for women, for foreigners, for workers under 26 and especially for workers over 55.

Results exhibit strong time-varying past state dependence. As expected, one additional month on employment during the past 6 months reduces the monthly probability of exiting employment. The previous year, we observe non linear duration dependence, as the risk of separation increases with the number of months spent out of employment in the just preceding 6 months, but decreases with the number of months spent out of employment in the former 6 months. In other words, the risk of separation is greater at the beginning of the employment contract and is then lower. The short-term effect, which is attenuated by the introduction of unobserved heterogeneity, may reveal unstable trajectories where non employment periods and short employment spells alternate. The longer term effect would on the contrary be due to an experience or tenure effect.

Previous participation in employment training reduces the risk of exiting employment, but only if participation occurred in the past 6 months. Older participation in this type of programme increases the monthly probability of entering the non employment state. This runs counter the argument of lasting accumulation of specific human capital during training. Several scenarii may explain this result. For example, workers on temporary contract participate in training at the beginning of their contract and accumulate specific human capital. Here, training participation increases the stability of the temporary contract, but only for a 6-month period. Another possible explanation is that firms offer training to their employees before firing them, or that employed individuals use training on the job to prepare a change in activity. A descriptive analysis of the motivations of the ending of the job runs along with the idea that during training, workers acquire general human capital they can export to other jobs: employment spells with training program end more frequently because of resignation than employment spells without training participation (respectively 33,9% and 24,2%).

To see the effect of previous out-of-employment training, we compare it with the effect of previous non employment periods. Even when we account for unobserved heterogeneity, a worker who was not employed during the previous year has a greater risk of separation than a worker who participated in out-of-employment training during the previous year. This positive effect of out-of-employment training on employment stability is observed only for recent participations.

4.4 Impact of training on reemployment probability and on non employment duration

Lastly, we interpret here the determinants of the monthly probability of transition from non employment to employment, that is, the determinants of the non employment duration (Table B1). As expected, the probability of reemployment increases with the level of education and sharply decreases with the age of the worker. Moreover, women and foreigners have a lower monthly probability of reemployment.

The estimates show the usual negative state and duration dependence of non employment: the time spent on employment in the just preceding 6 months increases the monthly probability of reemployment. More interestingly, the more the worker spent time in employment training during the previous year, the higher is her/his probability of reemployment. This positive effect is only significant for recent participation. It reveals the interest of distinguishing longer term effects from short term effects of training on the labour market history. Lastly, the more the individual spent time in out-of-employment training during the past 12 months, the higher is her/his probability to find a job quickly. This positive effect remains significant when we account for unobserved heterogeneity, although attenuated. It is only significant for older participation in training programme. This means that out-of-employment training reduces the non employment duration some time after the training is completed.

5 Simulations

To have a clearer understanding of the effect of participation in training programmes on labour market histories, we proceed to simulations. We simulate and compare the evolutions of the share of employed workers depending on two factors: participation or not in training programmes during the first year and the possibility or not to reenter such programmes later. Simulations are implemented using two sets of Monte Carlo experiments. Each MC experiment consists to draw randomly with replacement 1000 samples of size N. For each individual and each sample, a trajectory on the labour market is drawn randomly conditional on the initial conditions and on the value of individual characteristics. The labour market transitions are obtained using the parameters of the estimated model with a continuous distribution for the unobserved heterogeneity.

Results show that training during employment increases mobilities and that there are time-varying effect of employment training on the employment rate.

Figure 1 shows the effect of employment training for individuals that are initially employed for one year. Controls are in open employment during the first year and can never enter a training programme. Treated are in open employment for 6 months and then participate in an employment training programme. Contrary to the controls, they can reenter a programme later on. The graphes shows how the difference in employment rates between treated and controls evolves after this initial year. We observe that employment training increases employment stability for about 5 months. Then, workers who have access to training and who were trained on the job have a lower employment probability than the others. The difference between treated and untreated increases between 6 and 12 months after participation and then starts vanishing. For programmes of different durations, we observe the same timing of events, but different magnitudes in the effect, the negative effect of employment training observed after month 5 being greater for longer employment training programmes.

The graph on the left in Figure 2 shows that, if we invert the sequence of treatment in the initial year and force treated individuals to remain employed after participation in the employment training programme, then employment training has a positive although insignificant effect on the employment rates. However, the graph on the right in Figure 2 shows a positive effect of previous participation in employment training for individuals that experience non employment. Here, we look at the evolution of the employment rates for individuals who have a 6-month period of non employment after either open employment or employment training. Treated individuals are first slightly less employed than controls, but after about 8 months, they have greater employment rate. This positive effect of about 5 percentage points remains lastly significant and stable.

[FIGURES 1 AND 2]

Concerning training during non employment, we also find time-varying effect on the employment rates. Results run along with existing studies.

Figure 3 looks at the effects of out-of-employment training for workers who are not employed for 12 months. On the graph on the left, both treated and controls are initially out of employment for 6 months. Treated then participate in a 6-month out-of-employment training period while controls remain in open non employment. There are significant positive mid-term effects of out-of-employment training, that first sharply increase and then decrease slowly. The initial negative lock-in effect during the first months reverses and the differences between treated and non treated becomes lastly and significantly positive. On the right-hand side graph of Figure 3, we reverse the sequence of event: treated participate in the programme in the first 6 months and are in open non employment the following 6 months. In this scenario, out-of-employment training has a monotonic positive but insignificant effect on the probability of employment. This may be due to the fact that we neutralize the short-run positive effect as we force the treated to have a 6-month period of non employment right after the treatment.

Lastly, we find positive impact of out-of employment training for workers that are not employed for a shorter period (Figure 4). Treated and controls are initially employed. Controls move to open non employment, while treated, who also become not employed, participate in a training programme when not employed. We can observe that the longer the training programme, the stronger the positive effect on employment rates and the stronger the initial lock-in effect.

[FIGURES 3 AND 4]

6 Conclusion

In this paper, we consider the impact of past participations in training programmes on the individual labour market mobility. Using a French survey, we consider jointly the effects of training programmes dedicated to employed workers and training programmes offered to individuals out of employment. We model the transitions between the states of the labour market using a multi-state multi-spell transitions model with unobserved heterogeneity. This allows to account for selection on observable and unobservables and to distinguish true from spurious state dependencies. The impact of the participation in training programs is considered *via* the number of months the individual have devoted to these programs during the previous year. We find that the conditional probability of reemployment is increasing with time spent during the previous year in training programmes, whatever the category of these programs. Surprisingly, past participation in employment training is associated with a greater hazard rate for the transition from employment to non employment, but it is also associated with a stronger reemployment probability. This indicates that employment training programmes is used to increase general human capital of workers. It is interesting to note that there is programme participation recurrence, even when unobserved heterogeneity is accounted for. As we control for observed and unobserved characteristics of the worker, this result indicates that previous participation in these programs may reveal the willingness of the worker to participate in such programs and his ability to benefit from it. Consequently, the employer or the public service of employment is more likely to offer training to workers who have already been trained. A further research could consist to distinguish the impact of the training programs according to the characteristics of the workers and to study the existence of a state dependence of a higher order.

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Appendix A Descriptive analysis

[FIGURES A1 AND A2]

Appendix B Results

[TABLES RESULTS B1 B2 AND B3]

Table 1: Descriptive statistics by training category

	Out-of-Employment Training	Employment Training	All training
N	1357(18.3%)	6080(81.7%)	7437
Type (%)			
In-work training	42.4	52.7	50.8
Internship/seminars	33.5	21.1	23.4
Self-training	3.7	1.8	2.1
Unknown	20.4	24.4	24.7
% Qualifying	21.3	9.4	11.6
% Specialized	74.7	75.0	74.9
Provider (%)			
Employer	2.9	21.3	17.9
Mix	1.4	0.8	0.9
PSE	32.7	1.8	7.4
State and local admin.	16.7	3.2	5.7
Individual	10.2	2.8	4.1
Unknown	36.1	70.1	64.0
Mean duration (in months)	5.0	2.6	3.1

Table 2: Sample composition

	All	Without training	With Employment training	With Out-of-Employment training
N	26077	20294	4914	1305
Female	53.94	55.64	44.61	64.52
Foreigner	16.20	7.51	3.22	7.20
Age				
<26	23.10	10.93	18.95	21.99
26-35	9.42	27.70	38.26	37.93
36-45	24.88	24.02	27.41	25.59
46-55	44.89	25.53	14.49	13.18
>55	13.66	11.82	0.90	1.30
Educational level				
None	6.73	27.83	12.74	23.07
<High school	12.70	46.66	38.01	41.46
High school	29.97	12.07	19.45	18.70
> High School	24.81	12.98	29.75	16.63

Table 3: **Transition matrix (number and %)**

$t \rightarrow$ $\downarrow (t-1)$		Empl.	Non Empl.	Empl. Training	Unempl. Training	Total (row)
Empl.	N	1035782	8993	5905	-	1050680
	%	98.58	0.86	0.56		100
Non Empl.	N	7794	462934	-	1273	472001
	%	1.65	98.08		0.27	100
Empl. Training	N	6483	-	26444	-	32927
	%	19.70		80.31		100
Non Empl. Training	N	-	1400	-	7632	9032
	%		15.15		84.50	100

Figure 1: Effect of recent employment training

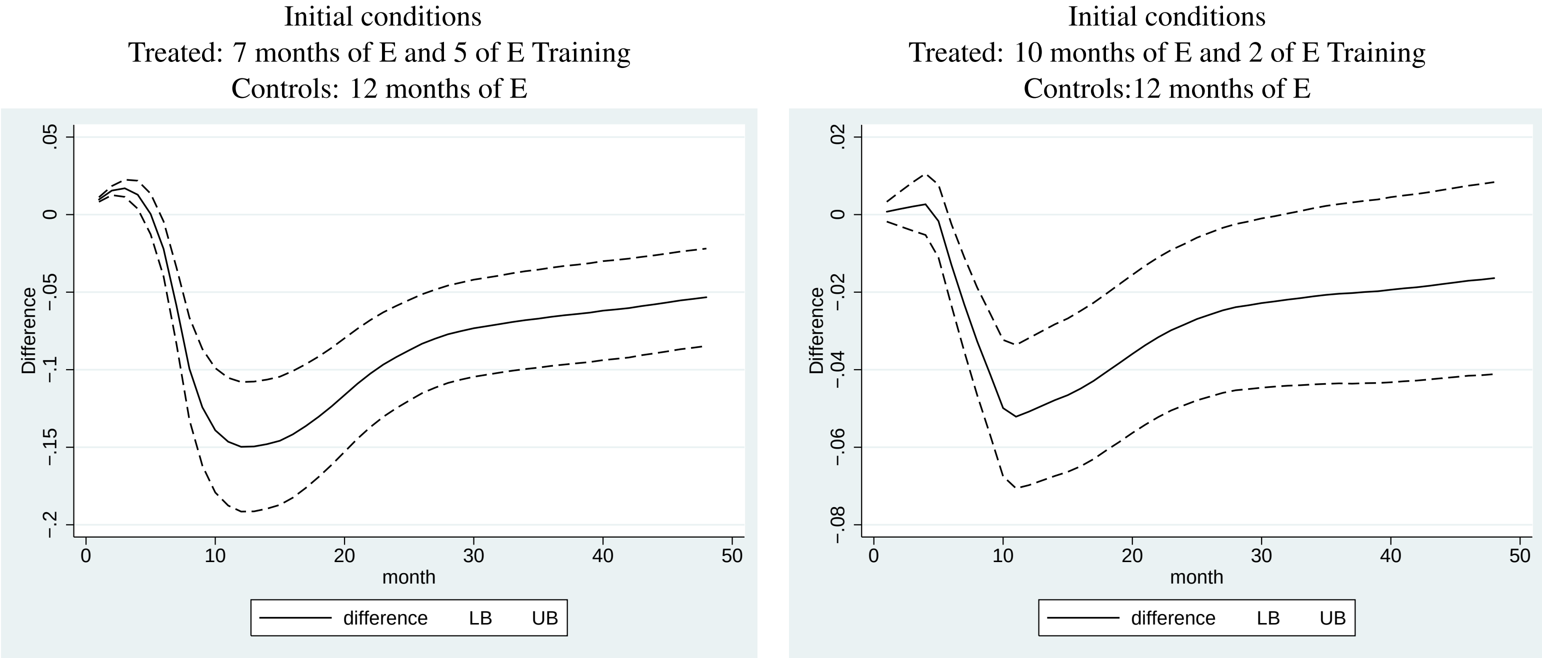
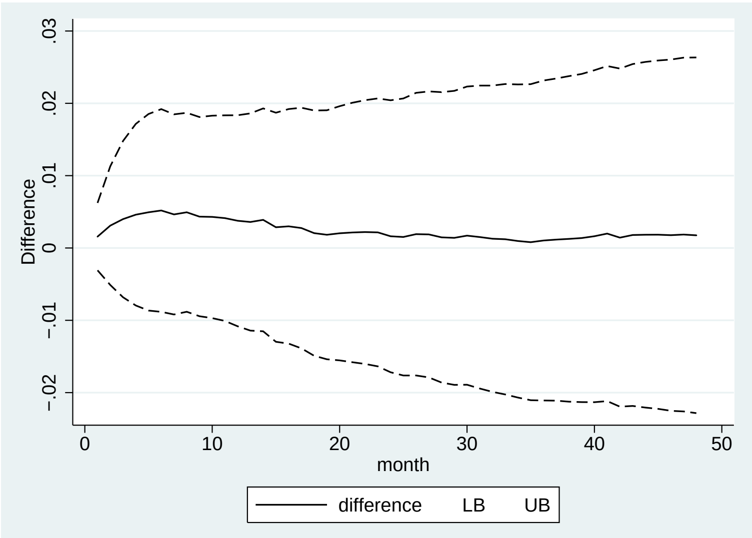


Figure 2: Effect of older employment training

Initial conditions
Treated: 6 months of E Training and 6 of E
Controls: 12 months of E



Initial conditions
Treated: 6 months of E Training and 6 of NE
Controls: 6 months of E and 6 of NE

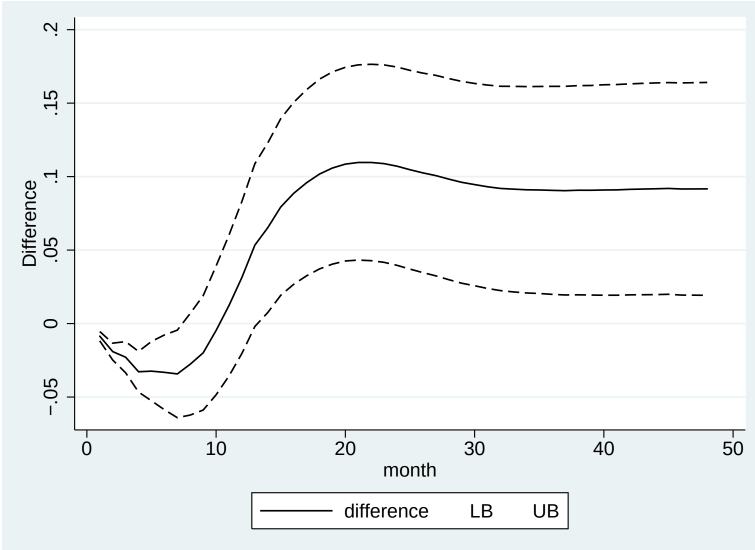


Figure 3: Effect of out-of-employment training for long-term non employed

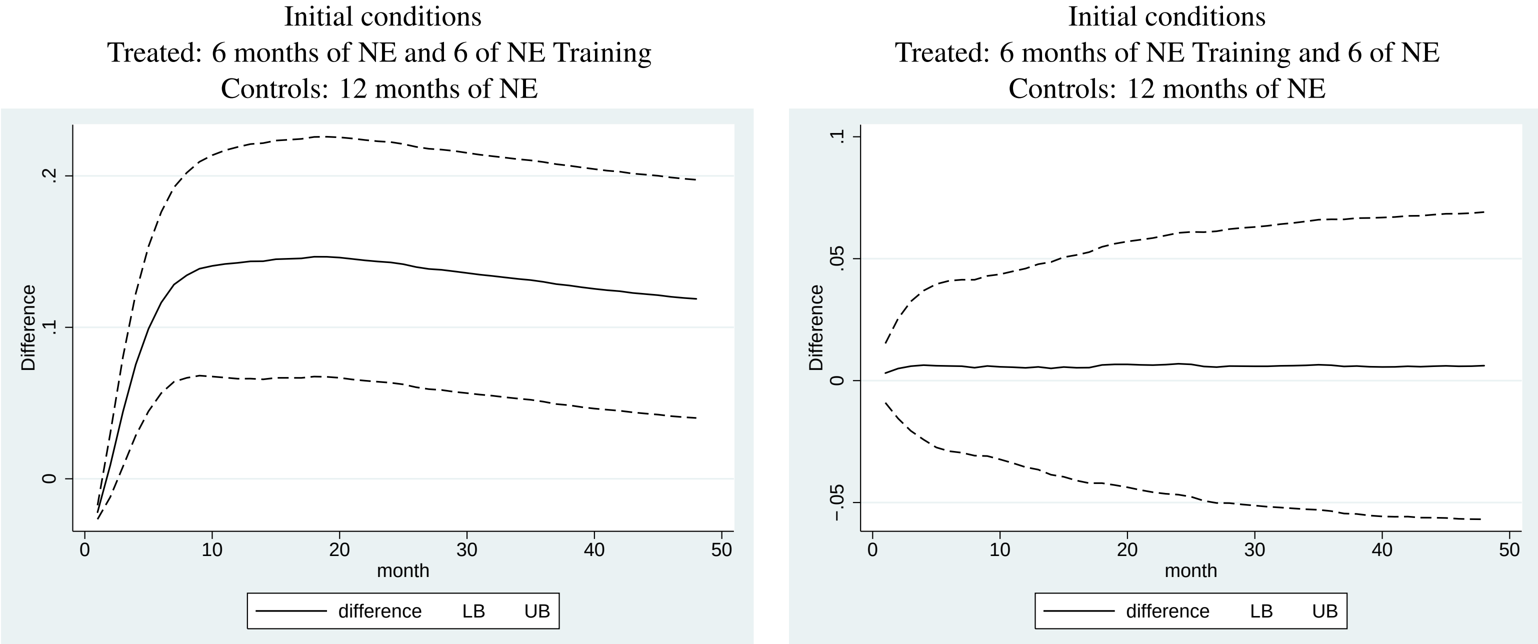
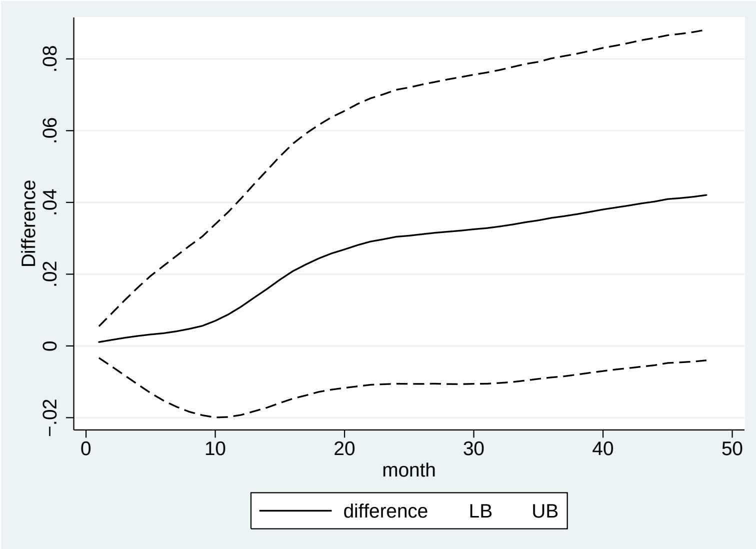
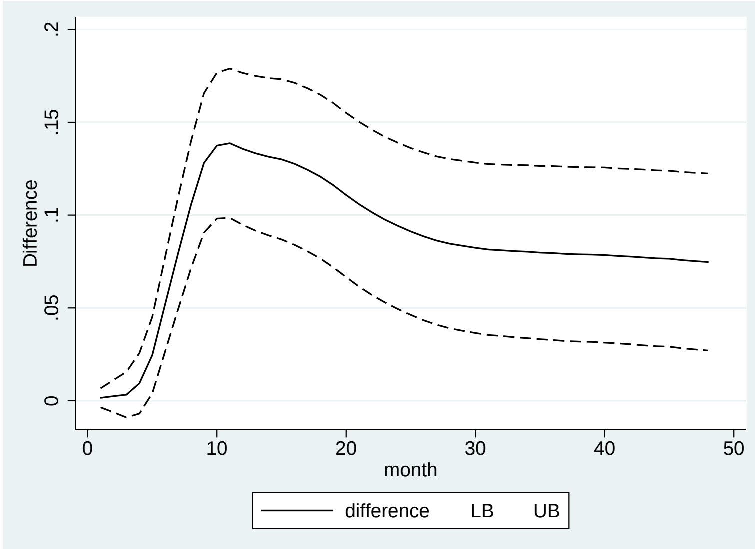


Figure 4: Effect of out-of-employment training for short-term non employed

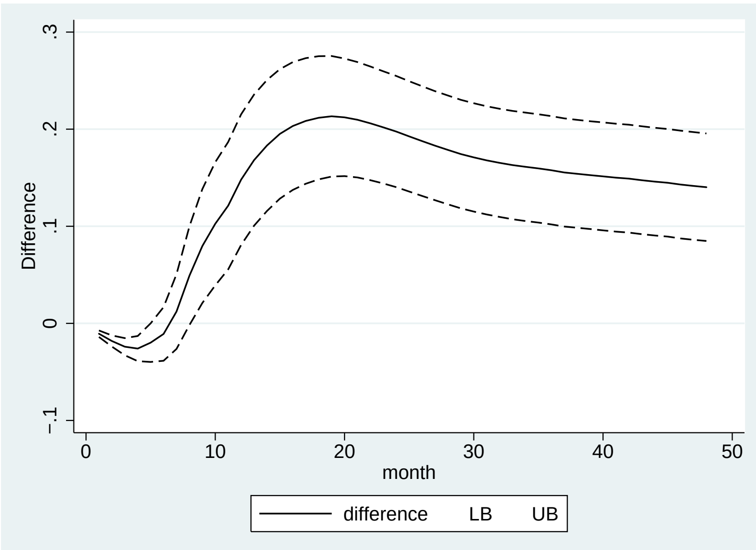
Initial conditions
Treated: 7 months of E, 3 of NE and 2 of NE Training
Controls: 7 months of E and 5 of NE



Initial conditions
Treated: 7 months of E, 2 of NE and 3 of NE Training
Controls: 7 months of E and 5 of NE



Initial conditions
Treated: 7 months of E, 1 of NE and 4 of NE Training
Controls: 7 months of E and 5 of NE



Initial conditions
Treated: 7 months of E and 5 of NE Training
Controls: 7 months of E and 5 months of NE

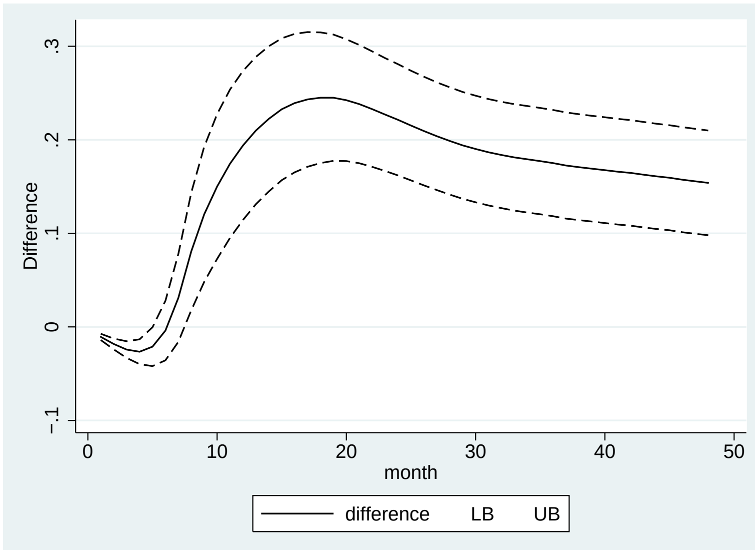


Figure A1: Kaplan Meier estimates of the survival function of the employment (left) and non employment (right) spells durations - stratification depending on whether there is participation in a training during the spell

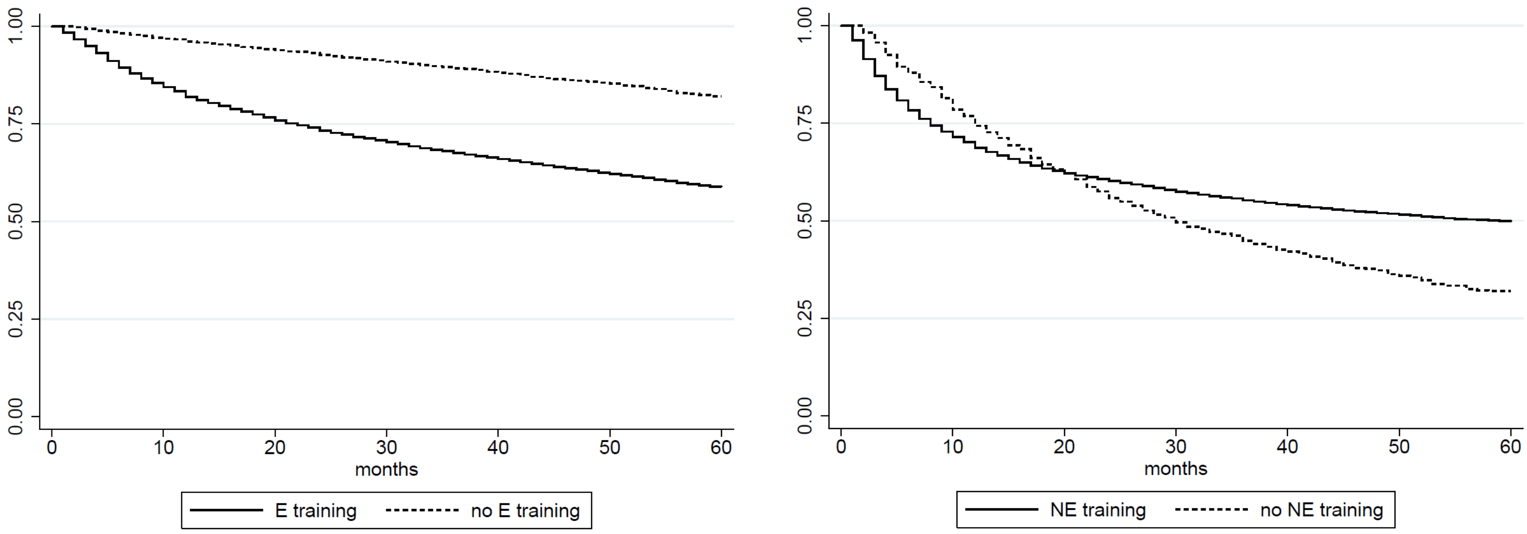


Figure A2: Kaplan Meier estimates of the survival function of the employment (left) and non employment (right) spells durations - stratification depending on whether there is participation in a training before the spell starts

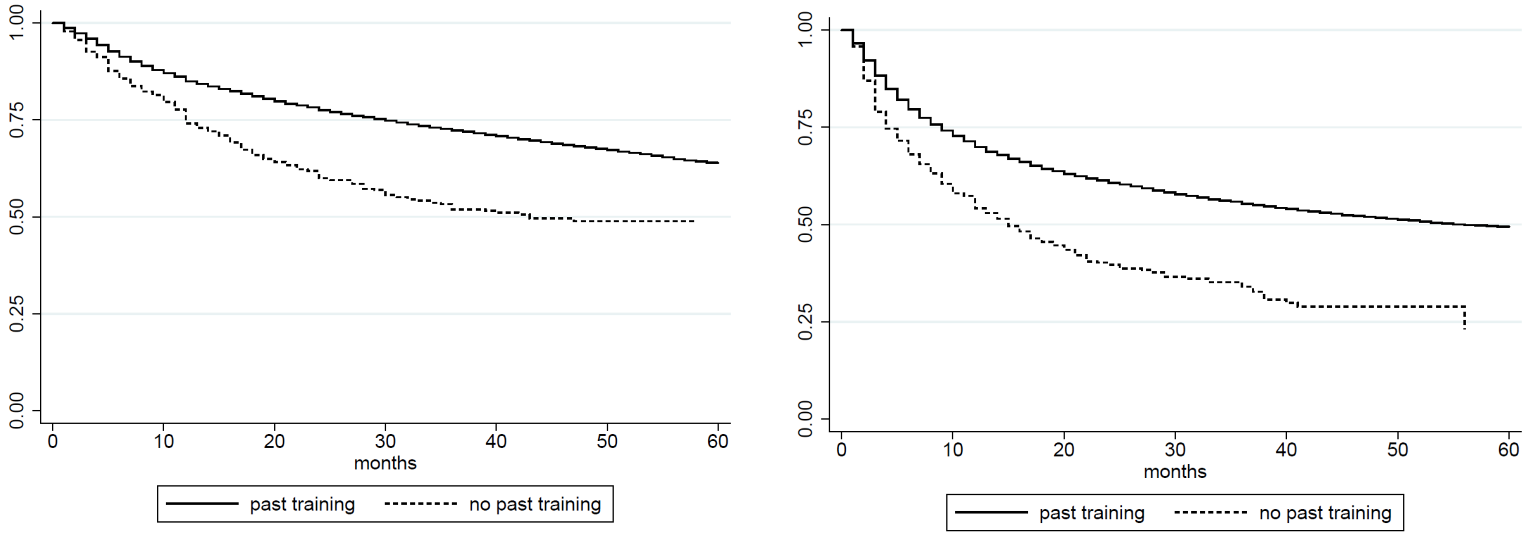


Table B1: Parameter estimates - transitions between employment and non employment

	(1) E to NE			(2) NE to E		
	(1a) no uh	**(1b) npara**	**(1c) para**	**(2a) no uh**	**(2b) npara**	**(2c) para**
Intercept	-4.505 ***	-3.703 ***	-4.770 ***	-3.089 ***	-1.913 ***	-3.322 ***
	(0.031)	(0.062)	(0.041)	(0.044)	(0.075)	(0.056)
Educational level (ref: none)						
< High School	-0.216 ***	-0.220 ***	-0.233 ***	0.359 ***	0.444 ***	0.413 ***
	(0.033)	(0.047)	(0.040)	(0.037)	(0.051)	(0.046)
High School	-0.184 ***	-0.188 ***	-0.208 ***	0.240 ***	0.295 ***	0.267 ***
	(0.026)	(0.036)	(0.031)	(0.029)	(0.040)	(0.035)
> High School	-0.517 ***	-0.550 ***	-0.586 ***	0.418 ***	0.513 ***	0.464 ***
	(0.035)	(0.048)	(0.041)	(0.039)	(0.051)	(0.049)
Female	0.298 ***	0.332 ***	0.350 ***	-0.516 ***	-0.539 ***	-0.513 ***
	(0.021)	(0.029)	(0.026)	(0.025)	(0.035)	(0.031)
Not French	0.118 ***	0.128 **	0.174 ***	-0.307 ***	-0.312 ***	-0.292 ***
	(0.041)	(0.056)	(0.050)	(0.047)	(0.060)	(0.056)
Age (ref: <26)						
26-35	-0.564 ***	-0.596 ***	-0.619 ***	-0.249 ***	-0.347 ***	-0.357 ***
	(0.028)	(0.040)	(0.035)	(0.030)	(0.041)	(0.040)
36-45	-0.855 ***	-0.964 ***	-0.949 ***	-0.524 ***	-0.721 ***	-0.679 ***
	(0.032)	(0.045)	(0.038)	(0.033)	(0.048)	(0.043)
46-55	-0.537 ***	-0.562 ***	-0.611 ***	-1.758 ***	-2.025 ***	-1.996 ***
	(0.033)	(0.047)	(0.041)	(0.040)	(0.058)	(0.049)
55+	0.876 ***	1.107 ***	1.110 ***	-4.470 ***	-4.723 ***	-4.724 ***
	(0.047)	(0.061)	(0.071)	(0.126)	(0.168)	(0.135)
State dependence : during [t-6.t-1]. nber of months in ... (ref: E (1) or NE (2))						
NE	0.226 ***	0.146 ***	0.170 ***			
	(0.007)	(0.009)	(0.008)			
E				0.169 ***	0.126 ***	0.117 ***
				(0.007)	(0.008)	(0.007)
E training	-0.043 **	-0.062 ***	-0.039 *	0.178 ***	0.116 ***	0.126 ***
	(0.022)	(0.022)	(0.022)	(0.029)	(0.030)	(0.031)
NE training	0.129 ***	0.064 *	0.063 *	0.033 *	0.028	0.016
	(0.033)	(0.036)	(0.034)	(0.018)	(0.020)	(0.019)
State dependence : during [t-12.t-7]. nber of months in ... (ref: E(1) or NE (2))						
NE	-0.213 ***	-0.223 ***	-0.210 ***			
	(0.018)	(0.020)	(0.017)			
E				-0.128 ***	-0.181 ***	-0.149 ***
				(0.015)	(0.016)	(0.015)
E training	0.411 ***	0.416 ***	0.447 ***	-0.023	-0.097	-0.051
	(0.042)	(0.042)	(0.042)	(0.094)	(0.090)	(0.101)
NE training	-0.065	-0.089	-0.086	0.443 ***	0.388 ***	0.397 ***
	(0.112)	(0.101)	(0.114)	(0.031)	(0.036)	(0.032)
Unobserved heterogeneity						
Initial conditions (1st year) : nber of months in (ref: E)						
NE	0.059 ***	0.072 ***	0.055 ***	-0.038 ***	-0.037 ***	-0.025 ***
	(0.003)	(0.004)	(0.004)	(0.003)	(0.004)	(0.004)
E training	0.024 ***	0.034 ***	0.017 **	0.009	0.030 ***	0.015
	(0.007)	(0.009)	(0.008)	(0.009)	(0.011)	(0.012)
NE training	0.070 ***	0.070 ***	0.078 ***	0.008	0.027 **	0.049 ***
	(0.010)	(0.014)	(0.013)	(0.008)	(0.011)	(0.011)
λ		-0.147 ***	-0.345 ***		-0.790 ***	-0.043
		(0.047)	(0.025)		(0.040)	(0.029)
μ		-1.029 ***	-0.821 ***		-0.655 ***	-0.861 ***
		(0.023)	(0.023)		(0.027)	(0.026)

Table B2: Parameter estimates - transitions out of training

	(1) From E training to E			**(2) From NE training to NE**		
	(1a) no uh	**(1b) npara**	**(1c) para**	**(2a) no uh**	**(2b) npara**	**(2c) para**
Intercept	0.197***	-0.109	-0.742***	-1.495 ***	-1.131 ***	-1.741 ***
	(0.054)	(0.108)	(0.089)	(0.134)	(0.150)	(0.152)
Educational level (ref: none)						
< High School	-0.151***	-0.107	-0.103	-0.114	0.024	-0.081
	(0.050)	(0.074)	(0.078)	(0.104)	(0.106)	(0.109)
High School	-0.072	-0.052	-0.054	0.107	0.242 ***	0.151 *
	(0.047)	(0.069)	(0.073)	(0.077)	(0.090)	(0.084)
> High School	-0.216***	-0.176**	-0.106	-0.210 **	-0.064	-0.169
	(0.047)	(0.070)	(0.074)	(0.097)	(0.110)	(0.104)
Female	-0.366***	-0.382***	-0.528***	-0.053	-0.117	-0.084
	(0.026)	(0.039)	(0.042)	(0.064)	(0.072)	(0.069)
Not French	-0.080	-0.100	-0.257**	-0.139	-0.111	-0.128
	(0.074)	(0.122)	(0.105)	(0.109)	(0.127)	(0.116)
Age (ref: <26)						
26-35	0.116***	0.060	0.125**	0.061	0.001	0.041
	(0.035)	(0.052)	(0.055)	(0.087)	(0.086)	(0.089)
36-45	0.145***	0.100*	0.197***	0.034	-0.027	0.036
	(0.039)	(0.057)	(0.060)	(0.089)	(0.093)	(0.092)
46-55	0.294***	0.241***	0.389***	0.142	-0.102	0.017
	(0.043)	(0.066)	(0.073)	(0.105)	(0.125)	(0.111)
55+	0.067	-0.090	0.071	-0.978 ***	-1.249 ***	-1.136 ***
	(0.117)	(0.205)	(0.236)	(0.266)	(0.325)	(0.296)
State dependence : during [t-6.t-1]. nber of months in ... (ref: E (1) or NE (2))						
NE	0.016	0.055**	0.009			
	(0.018)	(0.025)	(0.022)			
E				0.039 **	0.018	0.020
				(0.020)	(0.021)	(0.020)
E training	0.001	0.002	0.041***	-0.073 **	-0.080 **	-0.068 *
	(0.009)	(0.011)	(0.010)	(0.036)	(0.040)	(0.037)
NE training	-0.033	-0.016	-0.027	-0.074 ***	-0.071 ***	-0.061 ***
	(0.037)	(0.050)	(0.045)	(0.019)	(0.020)	(0.020)
State dependence : during [t-12.t-7]. nber of months in ... (ref: E(1) or NE (2))						
NE	-0.177***	-0.249***	-0.191***			
	(0.046)	(0.064)	(0.055)			
E				-0.048	-0.069	-0.046
				(0.060)	(0.061)	(0.061)
E training	-0.421***	-0.272***	-0.266***	0.635 ***	0.638 ***	0.627 ***
	(0.016)	(0.021)	(0.018)	(0.090)	(0.101)	(0.092)
NE training	0.284***	0.302***	0.290***	0.054	0.066 *	0.050
	(0.085)	(0.112)	(0.104)	(0.036)	(0.037)	(0.037)
Unobserved heterogeneity						
Initial conditions (1st year) : nber of months in (ref: E)						
NE	-0.011***	-0.040***	-0.028***	-0.011	-0.016 **	-0.005
	(0.006)	(0.010)	(0.008)	(0.007)	(0.008)	(0.008)
E training	0.014***	0.001	0.010	-0.029 *	-0.020	-0.039 **
	(0.004)	(0.006)	(0.006)	(0.016)	(0.018)	(0.016)
NE training	-0.012	0.032	0.016	-0.011	-0.002	0.010
	(0.023)	(0.023)	(0.028)	(0.010)	(0.012)	(0.012)
λ		-0.857***	0.978***		-0.394 ***	-0.004
		(0.036)	(0.033)		(0.087)	(0.065)
μ		0.550***	-0.392***		-0.237 ***	-0.341 ***
		(0.063)	(0.037)		(0.065)	(0.049)

Table B3: Parameter estimates - transitions into training

	(1) From E to E training			**(2) From NE to NE training**		
	(1a) no uh	**(1b) npara**	**(1c) para**	**(2a) no uh**	**(2b) npara**	**(2c) para**
Intercept	-5.509 ***	-4.957 ***	-5.861 ***	-5.263 ***	-4.170 ***	-5.410 **
	(0.046)	(0.066)	(0.055)	(0.106)	(0.156)	(0.116)
Educational level (ref: none)						
$<$ High School	0.860 ***	0.907 ***	0.890 ***	0.608 ***	0.702 ***	0.671 **
	(0.043)	(0.057)	(0.048)	(0.091)	(0.103)	(0.096)
High School	0.450***	0.470***	0.465***	0.315***	0.376***	0.357**
	(0.040)	(0.051)	(0.043)	(0.076)	(0.084)	(0.080)
$>$ High School	1.065***	1.077***	1.112***	0.593***	0.698***	0.669**
	(0.041)	(0.053)	(0.047)	(0.096)	(0.105)	(0.102)
Female	-0.342***	-0.316***	-0.340***	-0.318***	-0.411***	-0.365**
	(0.024)	(0.031)	(0.028)	(0.064)	(0.071)	(0.068)
Not French	-0.450***	-0.453***	-0.467***	-0.147	-0.181	-0.165
	(0.072)	(0.087)	(0.081)	(0.113)	(0.122)	(0.121)
Age (ref: $<$26)						
26-35	-0.044	-0.085**	-0.050	0.007	-0.043	-0.033
	(0.033)	(0.043)	(0.041)	(0.080)	(0.086)	(0.085)
36-45	-0.084**	-0.147***	-0.097**	-0.015	-0.117	-0.104
	(0.036)	(0.047)	(0.044)	(0.087)	(0.096)	(0.092)
46-55	-0.407***	-0.491***	-0.437***	-1.113***	-1.380***	-1.294**
	(0.041)	(0.054)	(0.050)	(0.102)	(0.117)	(0.112)
55+	-1.051***	-1.126***	-1.160***	-3.326***	-3.667***	-3.516**
	(0.138)	(0.174)	(0.152)	(0.269)	(0.286)	(0.277)
State dependence : during [t-6.t-1]. nber of months in ... (ref: E (1) or NE (2))						
NE	-0.073***	-0.054***	-0.066***			
	(0.018)	(0.017)	(0.018)			
E				0.060***	0.038**	0.038**
				(0.019)	(0.019)	(0.019)
E training	0.147***	0.176***	0.169***	-0.139***	-0.133***	-0.092**
	(0.015)	(0.015)	(0.016)	(0.039)	(0.050)	(0.038)
NE training	-0.187***	-0.171***	-0.230***	0.191***	0.164***	0.149**
	(0.037)	(0.041)	(0.040)	(0.035)	(0.041)	(0.036)
State dependence : during [t-12.t-7]. nber of months in... (ref: E(1) or NE (2))						
NE	0.381***	0.333***	0.429***			
	(0.038)	(0.036)	(0.038)			
E				0.167***	0.103**	0.117**
				(0.040)	(0.041)	(0.041)
E training	-0.022	-0.130***	-0.115***	1.566***	1.517***	1.415**
	(0.036)	(0.037)	(0.036)	(0.074)	(0.103)	(0.073)
NE training	1.372***	1.281***	1.460***	0.127*	0.070	0.091
	(0.065)	(0.073)	(0.072)	(0.074)	(0.081)	(0.074)
Unobserved heterogeneity						
Initial conditions (1st year) : nber of months in (ref: E)						
NE	0.014***	-0.014**	0.009	-0.058***	-0.073***	-0.055**
	(0.005)	(0.006)	(0.006)	(0.007)	(0.008)	(0.008)
E training	0.092***	0.096***	0.109***	-0.007	0.004	0.010
	(0.004)	(0.006)	(0.005)	(0.015)	(0.019)	(0.017)
NE training	0.020	0.047**	0.037*	-0.002	0.021	0.040*
	(0.018)	(0.019)	(0.021)	(0.019)	(0.021)	(0.021)
λ		-0.877***	0.821***		-1.011***	0.490**
		(0.024)	(0.019)		(0.066)	(0.064)
μ					-0.097	-0.657**
					(0.081)	(0.060)