Does training boost the job finding rate of the unemployed ? Timing-of-events based evidence from Belgium

Muriel Fonder[1] Bernard Lejeune[2] Ekaterina Tarantchenko[3]

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Abstract

This paper evaluates the effectiveness of the training programs offered to the unemployed in Wallonia, the French-speaking part of Belgium. More precisely, we are interested in the two following questions : (a) does training increase the job finding rate of the unemployed after the completion of their training ? (b) if so, is this increase big enough to compensate the so-called lock-in effect of their training ? To answer these questions, we rely on the Abbring and van den Berg (2003) timing-of-events approach and a very large administrative dataset. We find that training has an overall strong and persistent effect on the job finding rate of the unemployed after the completion of their training, but that this effect is heterogeneous, varying according to the characteristics of training and trainees. Further, we find that this effect on the job finding rate is globally large enough to compensate the lock-in effect of the training, but again with significant heterogeneity.

Keywords : Training, unemployment, policy evaluation, timing-of-events, discrete duration model.
JEL. classification : J24, J64, J68, C41.

[1] IWEPS, Route de Louvain-la-Neuve, 2, 5001 Namur, Belgium. Email : m.fonder@iweps.be
[2] Corresponding author : HEC-University of Liège, Place des Orateurs, 3, B31, 4000 Liège, Belgium. Email : b.lejeune@uliege.be
[3] Federal Planning Bureau, Avenue des Arts, 47-49, 1000 Bruxelles, Belgium, Email : te@plan.be

1. Introduction

Training programs are a major component of active labor market policies (ALMPs) in most OECD countries. They basically aim at improving the qualification of the unemployed in hope of boosting their employment probability.

Training programs are usually rather expensive. Yet, their effectiveness appears to be mixed. As a matter of fact, in a meta-analysis of more than 200 ALMP evaluation studies, Card et al. (2015) found as many evaluations where training programs have no significant – or even a negative – impact on trainees as evaluations that show a significant positive impact. The heterogeneity of results across studies certainly follows from differences regarding the way the impact is measured (unemployment duration, probability of employment at a given time horizon, level of earnings, ...) and the methodology. It certainly also stems from national differences regarding the details of the training programs (who is trained, for how long, ...) as well as the institutional framework in which they are implemented.

The purpose of this paper is to evaluate the effectiveness of the training programs offered to the unemployed in Wallonia, the French-speaking part of Belgium. More precisely, we are interested in the two following questions : (a) does training increase the job finding rate – the transition rate out of unemployment – of the unemployed after the completion of their training ? and (b) If so, is this increase big enough to compensate the so-called lock-in effect of their training, i.e., the fact the trainees temporarily pass up job opportunities while in training ?

This paper contributes to the literature investigating the effectiveness of training programs using the recent, duration model based, Abbring and van den Berg (2003) timing-of-events approach. This relatively small literature contains evaluations of training programs in Austria (Weber and Hofer (2004)), East Germany (Hujer et al. (2006a)), West Germany (Hujer et al. (2006b) and Osikominu (2013)), Switzerland (Lalive et al. (2008), France (Crépon et al. (2012)) and Sweden (Richardson and van den Berg (2013)). In line with the evaluation studies based on other approaches, this literature has so far produced mixed results. Regarding our first question, there is almost as many evaluations (Hujer et al. (2006a) for East Germany, Lalive et al. (2008) for Switzerland, and Crépon et al. (2012) for France) finding no significant – or even negative – effect of training on the job finding rate of the unemployed after the completion of their program as evaluations finding a significant positive effect (Weber and Hofer (2004) for Austria, Hujer et al. (2006b) and Osikominu (2013) for West Germany, and Richardson and van den Berg (2013) for Sweden). Regarding our second question, among the four studies who find a significant positive effect on the job finding rate of the unemployed after the completion of their program, two studies (Hujer et al. (2006b) and Osikominu (2013) for West Germany) find it to be big enough to compensate the lock-in effect of the training, but this is only for short training programs. As far as we know, this paper is the first one evaluating the effect of training in Belgium using the timing-of-events approach[1].

[1] The only other study evaluating the effect of training in Belgium we are aware of is Cockx (2003).

While in line with the available literature, our evaluation includes some noticeable features. First, it is based on a very large administrative dataset (around 185 000 observations), including multiple unemployment spells for many individuals and covariates containing individual characteristics and past employment history. Second, it allows the effect of training to be heterogeneous, varying according to when the training starts during the unemployment spell, the duration and the type of the training, the time elapsed since the completion of the training, as well as individual characteristics. Finally, from our estimated model parameters, we carefully and analytically evaluate the net effect of training – i.e., the effect of training, including its deleterious lock-in effect, compared to a relevant counterfactual without training – for the entire population and some subpopulations of the trainees, in terms of differences in median unemployment durations and probabilities of survival in unemployment as considered in Crépon et al. (2009).

In a nutshell, we find that training has an overall strong and persistent effect on the job finding rate of the unemployed after the completion of their training, but that this effect is heterogeneous, varying according to the characteristics of training and trainees. Further, we find that this effect on the job finding rate is globally large enough to compensate the lock-in effect of the training, but again with significant heterogeneity.

The rest of this paper is organized as follow. Section 2 describes the institutional background of training in Wallonia. Section 3 presents our data and provides some descriptive statistics. Section 4 discusses our empirical strategy relying on the timing-of-events approach. The results are presented in Section 5. Finally, Section 6 concludes.

2. Training in Wallonia

Belgium is a federal state composed of three regions. With respect to labour market policies, the federal government is in charge of the legislation and the unemployment insurance system. The regional authorities are in charge of the counseling and the training of the unemployed. In Wallonia, this task falls under the auspices of the FOREM (service public wallon de l'EMploi et de la FORmation), the regional public employment and training service.

The unemployment rate in Wallonia is rather high. According to the Eurostat Labour Force Surveys, over the period 1999 to 2016, it was on average equal to 10.7%, with a minimum of 8.5% reached in 2002. Yet, the participation rate of the unemployed in training is rather low : in 2011, which is the last year of observation of our study, only 6.3% of the unemployed aged 25-64 participated in a training program, which is far below the European Union average (9.5%). It is also well below the 1997 European Council in Luxemburg recommendation to place 20% of the unemployed into training or other equivalent active employment programs.

The trainings are provided by the FOREM and its (mostly non-profit) subcontractors. Two types of training are offered to the unemployed : vocational training and non-vocational training. Vocational training aims at providing skills and knowledge required for a particular profession. The goal of non-vocational training is to enhance general skills such as literacy, mathematics or language. Such non-vocational training is in some cases a prerequisite for being able to follow a vocational training. Generally speaking, the duration of a training may vary from one week to over a year.

Participation to a training may in some special cases be compulsory, but it is most of the time voluntary. Available trainings are advertised through the caseworkers, the FOREM (and subcontractors) website and decentralized contact points. Interested individuals are invited to a collective meeting where they are informed about the targeted job, the content of the training as well as the access requirements for the training.

In principle, any unemployed individual may apply for a training. The actual enrollment usually depends on an evaluation test and/or a selection/motivation interview, as well as on the number of available places. Some training may require a minimum education level or some prerequisites such as language or arithmetic proficiency. Also, the caseworker of the applicant may be asked to provide a summary report on the aptitude of the jobseeker to undergo the training.

During a training, the unemployed are globally exempted to actively look for a job, but must in principle remain available for employment, if a proper job opportunity shows up. Trainings are offered free of charge. In addition, training participants receive an allowance equal to 1 euro per hour of training, and may benefit from further financial compensations such as an allowance for child care or a reimbursement of travel expenses.

3. Data

This study relies on data obtained from the Crossroads Bank for Social Security, a public agency gathering administrative micro-data from various public institutions. In the present case, data were gathered from the FOREM, the National Register and the National Social Security Office.

Our dataset consists of a 80% random sample of all individuals aged 25-49 who started a new unemployment spell between January 2008 and December 2010. By definition, an individual is considered as starting a new unemployment spell when he registers as unemployed jobseeker at the FOREM after a period of at least three consecutive months without having been registered as unemployed. All sampled individuals are followed until December 2011, so that they are observed over a period varying from 1 to 4 years. If an originally sampled individual registers again as unemployed jobseeker at the FOREM[2] before the end of the observation window (i.e., before December 2011), then a second new unemployment spell is recorded for this individual, and so on if he subsequently again registers as unemployed, so that each sampled individual may be observed to have multiple unemployment spells within the January 2008 - December 2011 observation window[3]. Overall, our sample

[2] Likewise after a period of at least three consecutive months without having been registered as unemployed.

[3] Of course, those subsequent spells which start during the last year of the observation window (i.e., 2011) are observed over less than one year.

is composed of 144 297 individuals and 185 851 unemployment spells (about 1.3 spells per individual).

An unemployment spell is defined as ending when the unemployed finds a job – which has to be immediately declared to the National Social Security Office by the employer –, regardless of the job duration. Ongoing spells at the end of the observation window are censored[4].

For each unemployment spell, we know whether or not the unemployed has followed a training within the observation window, and if he did, when the training started and how long it lasted. Training participation is identified by the period during which the unemployed receives a training allowance. When more than one training is observed during the spell, only the first one is considered. Overall, among the 185 851 unemployment spells observed, 15 169 – i.e., about 8.2% – include a training episode. Table 1 summarizes the composition of our sample.

Table 1 : Sample composition

	First spell	All spells
Number of individuals	144 297	144 297
Number of spells	144 297	185 851
Individuals with exactly 1 spell (%)	76.0	
Individuals with exactly 2 spells (%)	19.9	
Individuals with at least 3 spells (%)	4.1	
Spells with training (#)	13 332	15 169
Spells with training (%)	9.2	8.2
Censored spells (%)	32.8	33.8

Beside entry to and exit from unemployment and training, which are recorded on a weekly basis due to privacy laws, our dataset contains information on individual characteristics (gender, age, education, sub-region of residence) and past employment history (number of quarters in employment over the last 2.5 years, self-employed or employee, wage and sector of activity). The data also includes the type of training (vocational versus non-vocational) and calendar time (allowing to control for calendar effects). Table 2 provides summary statistics on some of these covariates, contrasting spells without and with training.

Table 2 suggests that women receive training (slightly) more often than men. Differences regarding (mean) age are either nonexistent or very small. Regarding education, it appears that individuals with upper secondary education receive training less often than individuals with lower education (primary school and lower secondary) and, to a smaller extent, individuals with higher education. Also, individuals with shorter past employment appear to receive training more often than individuals with longer past employment. Overall, these differences are however not overwhelming. Finally, Table 2 outlines that about 66% of all observed training

[4] If an unemployed leaves the register of the unemployed jobseekers for any other reason than for a job (e.g., withdraw from the labour force for health or family reasons), his unemployment spell is likewise treated as censored.

episodes consists of vocational training.

Table 2 : Unemployment spells, without and with training

	First spell		All spells	
	No training	Training	No training	Training
Men (%)	48.5	47.2	47.8	47.4
Women (%)	51.5	52.8	52.2	52.6
Mean age (years)	34.5	34.5	34.9	34.6
Primary school and lower secondary (%)	54.4	56.7	54.2	56.3
Upper secondary (%)	28.6	25.8	28.7	25.8
Higher education (%)	17.0	17.5	17.2	17.8
Mean past employment (quarters)	5.0	4.4	5.0	4.4
Vocational training (%)	-	65.8	-	66.3
Non-vocational training (%)	-	34.2	-	33.7
Observations	130 965	13 332	170 682	15 169

Note : Past employment is the number of quarters in employment over the last 2.5 years.

Table 3 further reports some summary statistics about all observed training episodes (all spells with training), contrasting vocational and non-vocational training. While differences regarding (mean) age are again very small, Table 3 shows that non-vocational training is much more received by women than men, by individuals with lower education than higher education, and by individuals with shorter past employment than longer past employment. Table 3 also outlines that non-vocational trainings tend to start somewhat later in the unemployment spell and to last much longer than vocational trainings.

Table 3 : Training episodes (all spells with training)

	Training episodes		
	Vocational	Non-vocational	All
Men (%)	55.3	31.9	47.4
Women (%)	44.7	68.1	52.6
Mean age (years)	34.5	34.9	34.6
Primary school and lower secondary (%)	43.0	82.5	56.3
Upper secondary (%)	31.4	14.9	25.8
Higher education (%)	25.6	2.6	17.8
Mean past employment (quarters)	5.3	2.6	4.4
Median unemployment duration until training (weeks)	21	25	22
Median duration of training (weeks)	6	16	9
Observations	10 053	5 166	15 169

Note : Past employment is the number of quarters in employment over the last 2.5 years.

To complete our review of the data, Figure 1 displays Kaplan-Meier estimates of the weekly hazard rates – i.e., weekly transition rates – from unemployment to job and to training, based on all spells of our sample.

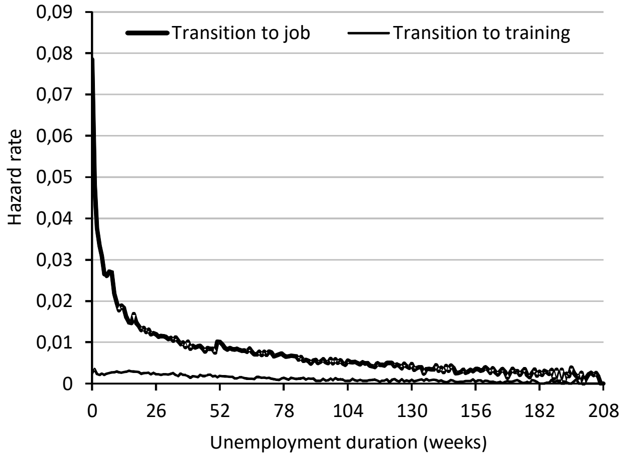

Figure 1 : Weekly transition rates to job and to training

Figure 1 shows that the job finding rates at first sharply decrease – from about a high 8% to around 1.5% – over the first 3 months (13 weeks) of unemployment, and then slowly and steadily decrease to reach approximately 0.3% after about 3 years (156 weeks) of unemployment. For their part, the rates of access to training appears to slowly and steadily decrease over the entire unemployment spell, starting from around 0.3% to reach on average less than 0.05% after more than 3 years of unemployment.

Finally, Figure 2 further displays Kaplan-Meier estimates of the weekly hazard rates from unemployment to job, this time contrasting (all) spells without and with training.

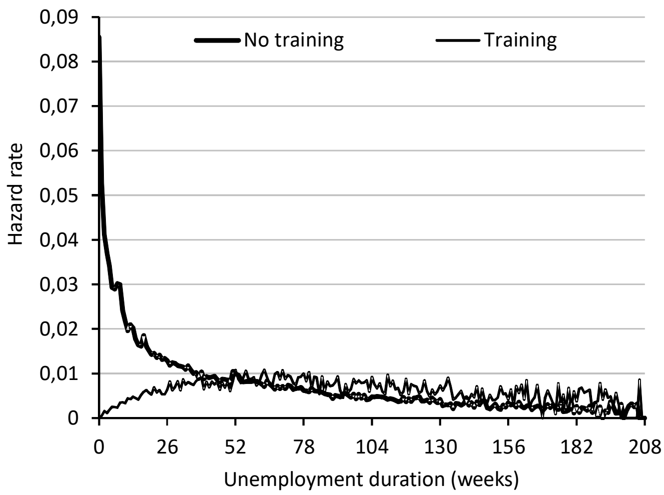

Figure 2 : Weekly transition rates to job, without and with training

Unsurprisingly, the job finding rates of the non-trainees – i.e., the job finding rates associated with the unemployment spells without training – are very much like as shown in Figure 1 for the entire sample[5]. Likewise, it should not be a

[5] As a reminder, unemployment spells without training account for more than 90% of all unemployment

surprise that the job finding rates of the trainees – i.e., the job finding rates from the unemployment spells with training – are initially very low. This is because an individual may only receive a training if he has not yet found a job, and because training takes time, during which the unemployed temporarily no longer actively looks for a job. However, as time elapses, more and more of the trainees actually start and eventually complete their training, so that the job finding rates accordingly gradually increase. Figure 2 shows that after a year (52 weeks) or so, the job finding rates of the trainees turn out to become larger than those of the non-trainees. This clearly suggests that training have a positive impact on the job finding rate of the unemployed. For a proper evaluation, a closer examination is however needed.

4. Empirical strategy

To properly evaluate whether training has a positive impact on the job finding rate of the unemployed, and beyond if this hopefully positive impact is large enough to compensate the lock-in effect of the training, we need to carefully account for the timing of training (when it starts, how long it lasts) and the (dynamic) selection of the unemployed into training, which may depend on both observed and unobserved individual characteristics, so that the job finding rates of the trainees are in effect compared to the job finding rates of properly time-aligned and comparable non-trainees. This can be achieved by using the recent, duration model based, Abbring and van den Berg (2003) timing-of-events approach.

4.1. Model specification and estimation

In a nutshell, following Abbring and van den Berg (2003), our empirical strategy relies on the joint modelling of the duration until a transition to a job and the duration until an entry into training. The effect of a training is captured by allowing training to affect the job finding rates of the trainees after the completion of their training. The (dynamic) selection of the unemployed into training is controlled by allowing both the job finding rates and the rates of access to training to depend on observed individual characteristics and (possibly correlated) transition-specific unobserved individual effects.

More formally, let T_u and T_p stand for the duration from the start of unemployment until, respectively, a transition to a job and an entry into a training program. As entry to and exit from unemployment and training are recorded on a weekly basis in our data, T_u and T_p are modelled in discrete time[6]. The transition rates from unemployment to job and the access rates to training are assumed to be respectively

spells.

[6] The possible values of T_u and T_p are assumed to be $t = 0, 1, 2, ...$, $t = 0$ denoting the week when the unemployment spell starts, $t = 1$ the first next week, $t = 2$ the second next week, and so on.

given by the (conditional) hazard functions:

$$\begin{aligned} h_u(t|t_p, d_p, x, V_u) &= I\!P\left[T_u = t | T_u \geq t, T_p = t_p, d_p, x, V_u\right], \quad \forall\, t = 0, 1, 2, ... \\ &= g\left[\lambda_u(t) + x'\beta_u + \delta(t|t_p, d_p, x)\, I(t \geq t_p + d_p) + V_u\right] \qquad (1) \\ &\quad \times (1 - I(t_p \leq t < t_p + d_p)) \end{aligned}$$

and

$$\begin{aligned} h_p(t|x, V_p) &= I\!P\left[T_p = t | T_p \geq t, x, V_p\right], \quad \forall\, t = 0, 1, 2, ... \\ &= g\left[\lambda_p(t) + x'\beta_p + V_p\right] \qquad (2) \end{aligned}$$

where $g[.]$ stands for a positive monotonic function and $I(.)$ is an indicator function taking the value 1 when its argument is true, and 0 otherwise.

The hazard function $h_u(t|t_p, d_p, x, V_u)$ specifies the job finding rate – i.e., the probability of finding a job at period t, while still unemployed at period $t-1$ – of an unemployed as a function of the time elapsed from the start of his unemployment spell ($= t$), the starting time ($= t_p$) and duration ($= d_p$) of his training program (if any), his observed individual characteristics[7] ($= x$), and an unobserved individual effect ($= V_u$). If the unemployed does not receive any training, which may be viewed as the same as assuming that $T_p = t_p = \infty$, his job finding rates are simply given by $h_u(.|.) = g\left[\lambda_u(t) + x'\beta_u + V_u\right]$. With $g[.]$ specified as the exponential function and $\lambda_u(t)$ representing the baseline hazard, this is the same as in a standard Mixed Proportional Hazard (MPH) model. If the unemployed receives a training, three regimes have to be distinguished. Before entering his training program at $T_p = t_p$, i.e., for all $t < t_p$, his job finding rates are assumed to be the same as the job finding rates of an unemployed who does not receive any training: $h_u(.|.) = g\left[\lambda_u(t) + x'\beta_u + V_u\right]$. During his training, i.e., for all t such that $t_p \leq t < t_p + d_p$, by definition of the data, his job finding rates are equal to zero. Finally, after the completion of its training, his job finding rates are given by $h_u(.|.) = g\left[\lambda_u(t) + x'\beta_u + \delta(t|t_p, d_p, x) + V_u\right]$, where the term $\delta(t|t_p, d_p, x)$ measures the effect of the training. Training has a positive effect on the job finding rate of the unemployed if $\delta(t|t_p, d_p, x) > 0$. The effect of the training $\delta(t|t_p, d_p, x)$ is allowed to depend on the starting time ($= t_p$) and duration ($= d_p$) of the training, the unemployed's characteristics ($= x$), as well as the time elapsed since the completion of the training ($= t - (t_p + d_p)$).

On the other hand, the hazard function $h_p(t|x, V_p)$ specifies the access rate to training – i.e., the probability of starting a training at period t, while still not having started a training at period $t-1$ – of an unemployed as a function of likewise the time elapsed from the start of his unemployment spell ($= t$), his observed individual characteristics ($= x$), and another unobserved individual effect ($= V_p$). With $g[.]$ specified as the exponential function and $\lambda_p(t)$ representing the baseline hazard, this is again the same as in a standard MPH model. The unobserved individual effect V_p may be correlated with the unobserved effect V_u which drives the job finding rates of the unemployed in (1). This possible correlation allows to control for the selection of the unemployed into training due to unobserved characteristics[8], and is the very

[7] In the application, x also includes calendar time dummies to control for calendar effects, so that x is actually time-varying.

[8] For the sake of the argument, suppose that training actually has no effect on the job finding rates of the

reason why the duration until a transition to job and the duration until an entry into training are jointly modelled.

Our primary interest lies in the estimation of the effect of training $\delta(t|t_p, d_p, x)$. In the application, $\delta(t|t_p, d_p, x)$ is specified as a linear piecewise constant function varying (through sets of dummies) with the starting time, duration and time elapsed since the completion of the training, as well as the type of the training and the gender, age and education of the trainee. The baseline hazards $\lambda_u(t)$ and $\lambda_p(t)$ are likewise specified as linear piecewise constant. To avoid problems, the function $g[.]$ is specified as the logistic function[9]. However, given the (very) low transition rates typically observed (see Figure 1 and 2), the hazard functions $h_u(.|.)$ and $h_p(.|.)$ may from a practical point of view simply be interpreted as in a standard MPH model[10].

The hazard functions $h_u(.|.)$ and $h_p(.|.)$ fully characterize the joint distribution of the durations T_u and T_p, conditional on observed characteristics and unobserved individual effects[11]. The joint distribution of T_u and T_p conditional on the observed characteristics only, which forms the basis for the maximum likelihood estimation of the model, is obtained by integrating out the unobserved individual effects with respect to their assumed distribution. In the application, as standard in the timing-of-events approach, it is assumed that the joint distribution of the unobserved effects V_u and V_p:

$$G(v_u, v_p) = I\!P[V_u = v_u, V_p = v_p] \tag{3}$$

is given by a discrete distribution, here with three and two points of support for respectively V_u and V_p – which means 6 possible values for the pair (v_u, v_p)[12] –, whose both the mass points and their joint probabilities are estimated[13].

In practice, the duration T_p until an entry into training is only observed if the entry into training happens before the exit to job, i.e., if $T_p \leq T_u = t_u$. Otherwise, the duration T_p is censored: it is merely observed that T_p exceeds T_u, i.e., that $T_p \geq t_u + 1$. Also, the duration T_u until a transition to a job is only observed if the transition to a job happens before the end of the observation window. Otherwise, the duration T_u is censored (it is merely observed that $T_u \geq c + 1$, where c is the censoring period[14]), and the duration T_p until an entry into training is similarly censored (it is merely observed that $T_p \geq c + 1$) if likewise no entry into training happens before the end of the observation window. Accounting for this censoring scheme, the contribution to the likelihood function of an individual i with m_i spells

unemployed, but that V_u and V_p are positively correlated, which means that the unemployed who get trained tend to have higher job finding rates (regardless of whether or not they receive a training), for example because they are more motivated. If not taken into account, this would lead to spuriously attribute the observed higher job finding rates of the trainees to their training, while it is actually due to their unobserved characteristics.

[9] i.e., as $g[x] = \frac{\exp(x)}{1+\exp(x)}$. This ensures that the hasards $h_u(.|.)$ and $h_p(.|.)$ are always between 0 and 1.

[10] This follows from the fact that for low (negative) values of x – and thus low (positive) values of $g[x]$ –, we have: $g[x] = \frac{\exp(x)}{1+\exp(x)} \approx \exp(x)$.

[11] More precisely, $h_u(.|.)$ and $h_p(.|.)$ characterize respectively the distribution of T_u given T_p and the marginal distribution of T_p, which in turn characterize the joint distribution of T_u and T_p.

[12] Allowing for 3 points of support for V_p turned out to be empirically irrelevant (overparametrized).

[13] In the estimation, the joint probabilites are parametrized through a one-to-one multinomial logit transformation to ensure that they all are between 0 and 1, and sum to 1.

[14] i.e., the last period of observation.

(indexed by s) observed over the observation window may be written as[15] :

$$l_i = \sum_{(v_u,v_p)} \left\{ \prod_{s=1}^{m_i} [h_u(t_{u_{is}}|t_{p_{is}}, d_{p_{is}}, x_{is}, v_u)]^{D_{u_{is}}} S_u(t_{u_{is}}|t_{p_{is}}, d_{p_{is}}, x_{is}, v_u) \times [h_p(t_{p_{is}}|x_{is}, v_p)]^{D_{p_{is}}} S_p(t_{p_{is}}|x_{is}, v_p) \right\} G(v_u, v_p)$$

where $\sum_{(v_u,v_p)}$ means summation over all possible values of the (v_u, v_p) pair, $t_{u_{is}}$, $t_{p_{is}}$, $d_{p_{is}}$ and x_{is} denote the observed value of respectively T_u, T_p, d_p and x for individual i in spell s ($s = 1, ..., m_i$), $D_{u_{is}}$ and $D_{p_{is}}$ are dummy variables equal to 0 if the durations $t_{u_{is}}$ and $t_{p_{is}}$ (respectively) are censored durations[16] and equal to 1 otherwise, and $S_u(.|.)$ and $S_p(.|.)$ are the (conditional) survival functions associated with respectively the hazard functions $h_u(.|.)$ and $h_p(.|.)$, which are given by :

$$\begin{aligned} S_u(t|t_p, d_p, x, V_u) &= I\!P[T_u \geq t | T_p = t_p, d_p, x, V_u], \quad \forall\, t = 1, 2, ... \\ &= \prod_{t^*=0}^{t-1} (1 - h_u(t^*|t_p, d_p, x, V_u)) \end{aligned} \tag{4}$$

and

$$\begin{aligned} S_p(t|x, V_p) &= I\!P[T_p \geq t | x, V_p], \quad \forall\, t = 1, 2, ... \\ &= \prod_{t^*=0}^{t-1} (1 - h_p(t^*|x, V_p)) \end{aligned} \tag{5}$$

with $S_u(t|t_p, d_p, x, V_u) = S_p(t|x, V_p) = 1$ for $t = 0$.

The overall log-likelihood function is simply obtained by summing $\log l_i$ over all observed individuals. With the different elements of the log-likelihood function parametrized as described above, the maximum likelihood estimation of the model involves over 120 parameters. The maximum likelihood estimates were computed using the Gauss Optmum routine with the BFGS algorithm and analytic first derivatives.

4.2. Net effect evaluation

To properly evaluate the net effect of training, we need to compare the remaining unemployment duration of the trainees from the start of their training – which thus includes the time spend in training – with the remaining unemployment duration from the same starting point which would have prevailed if the same trainees have actually not started a training (the counterfactual). If training has a positive impact on the job finding rate of the unemployed after the completion of their training – i.e., if the effect of the training $\delta(t|t_p, d_p, x)$ in (1) is positive – and if this positive effect is large enough to compensate the lock-in effect of the training, then the distribution of the remaining unemployment duration of the trainees should be found more favorable – e.g., featuring a smaller median duration – with training than

[15] See Lejeune (2013) for a detailed derivation for a similar discrete time model.

[16] When the durations T_u and/or T_p are censored, their observed value is by definition set to their censoring period + 1.

without training. Both these probability distributions are characterized by – and may thus be estimated from – the hazard functions (1)-(2) and the unobserved heterogeneity distribution (3).

Formally, let $T_u^R = T_u - t_p$ denote the remaining unemployment duration from the beginning of a training starting at t_p. The (conditional) density function of T_u^R may be written[17] :

$$\begin{aligned} f_u^R(t|t_p, d_p, x, V_u) &= I\!P\left[T_u^R = t|T_u \geq t_p, T_p = t_p, d_p, x, V_u\right], \quad \forall\, t = 0, 1, 2, ... \\ &= I\!P\left[T_u = t + t_p|T_u \geq t_p, T_p = t_p, d_p, x, V_u\right] \\ &= \frac{h_u(t + t_p|t_p, d_p, x, V_u)S_u(t + t_p|t_p, d_p, x, V_u)}{S_u(t_p|t_p, d_p, x, V_u)} \end{aligned} \tag{6}$$

The density function $f_u^R(t|t_p, d_p, x, V_u)$ gives the probability distribution of the remaining unemployment duration of a trainee who was still unemployed and started his training at t_p, whose training lasted d_p, and whose observed and unobserved individual characteristics are respectively equal to x and V_u.

The counterfactual of this probability distribution, i.e., the distribution of the remaining unemployment duration of the same trainee – still unemployed at t_p and with the same observed and unobserved characteristics –, if he actually did not start any training, is given by the (conditional) density function[18] :

$$\begin{aligned} \overline{f}_u^R(t|t_p, d_p, x, V_u) &= I\!P\left[T_u^R = t|T_u \geq t_p, T_p = \infty, d_p, x, V_u\right], \quad \forall\, t = 0, 1, 2, ... \\ &= I\!P\left[T_u = t + t_p|T_u \geq t_p, T_p = \infty, d_p, x, V_u\right] \\ &= \frac{h_u(t + t_p|\infty, d_p, x, V_u)S_u(t + t_p|\infty, d_p, x, V_u)}{S_u(t_p|\infty, d_p, x, V_u)} \end{aligned} \tag{7}$$

where $(T_p = \infty)$ means no training, and by definition :

$$h_u(t|\infty, d_p, x, V_u) = g\left[\lambda_u(t) + x'\beta_u + V_u\right], \quad \forall\, t = 0, 1, 2, ...$$

and

$$S_u(t|\infty, d_p, x, V_u) = \prod_{t^*=0}^{t-1} \left(1 - h_u(t^*|\infty, d_p, x, V_u)\right), \quad \forall\, t = 1, 2, ...$$

with $S_u(t|\infty, d_p, x, V_u) = 1$ for $t = 0$.

The density functions (6) and (7) provide distributions – with and without training – of the remaining unemployment duration T_u^R for a particular trainee, who got trained at a particular date and has particular observed and unobserved characteristics. For evaluating the net effect of training, we are interested in the distributions of the remaining unemployment duration for the entire population – or some subpopulation – of the trainees. These aggregate (marginal) probability distributions may be obtained by first integrating out the unobserved individual effect V_u from (6) and (7) – this provides probability distributions conditional on

[17] For a detailed derivation of the results outlined in this Section for a similar discrete time model, see again Lejeune (2013).

[18] Note that the value of d_p actually plays no role in this counterfactual density function.

(t_p, d_p, x) only –, and then averaging them using the observed values of (t_p, d_p, x) for the population – or some subpopulation – of the trainees[19].

For integrating out the unobserved individual effect V_u from (6) and (7), we can not simply use the unobserved heterogeneity distribution $G(v_u, v_p)$ outlined in (3), which represents the distribution of unobserved individual heterogeneity at the inflow into unemployment. As a matter of fact, due to dynamic selection, the trainees are not a random sample of the inflow population. The relevant unobserved individual heterogeneity distribution to be used is given by:

$$\begin{aligned} G^R(v_u, v_p|t_p, d_p, x) &= I\!P[V_u = v_u, V_p = v_p | T_u \geq t_p, T_p = t_p, d_p, x] \\ &= \frac{S_u(t_p|t_p, d_p, x, v_u) h_p(t_p|x, v_p) S_p(t_p|x, v_p) G(v_u, v_p)}{\sum\limits_{(v_u^*, v_p^*)} S_u(t_p|t_p, d_p, x, v_u^*) h_p(t_p|x, v_p^*) S_p(t_p|x, v_p^*) G(v_u^*, v_p^*)} \end{aligned} \tag{8}$$

so that for a population $\mathcal{P}$ of m trainees with observed values of (t_p, d_p, x) equal to $\{(t_{p_i}, d_{p_i}, x_i),\ i = 1, ..., m\}$, the aggregate probability distributions of the remaining unemployment duration T_u^R with and without training are respectively given by the density functions:

$$\begin{aligned} f_u^R(t|\mathcal{P}) &= I\!P\left[T_u^R = t|\mathcal{P} \text{ with training}\right], \quad \forall\, t = 0, 1, 2, ... \\ &= \frac{1}{m} \sum_{i=1}^{m} \sum_{(v_u, v_p)} f_u^R(t|t_{p_i}, d_{p_i}, x_i, v_u) G^R(v_u, v_p|t_{p_i}, d_{p_i}, x_i) \end{aligned} \tag{9}$$

and

$$\begin{aligned} \overline{f}_u^R(t|\mathcal{P}) &= I\!P\left[T_u^R = t|\mathcal{P} \text{ without training}\right], \quad \forall\, t = 0, 1, 2, ... \\ &= \frac{1}{m} \sum_{i=1}^{m} \sum_{(v_u, v_p)} \overline{f}_u^R(t|t_{p_i}, d_{p_i}, x_i, v_u) G^R(v_u, v_p|t_{p_i}, d_{p_i}, x_i) \end{aligned} \tag{10}$$

The probability distribution (9) and its counterfactual (10) may handily be compared by contrasting their central tendency, for example their median. If the median of (9) is found to be smaller than the median of its counterfactual (10), this means that training globally reduces the median (remaining) unemployment duration among the considered population $\mathcal{P}$ of trainees. A more informative way of comparing the probability distribution (9) and its counterfactual (10) is provided by contrasting their corresponding survival functions, which are respectively given by:

$$S_u^R(t|\mathcal{P}) = I\!P\left[T_u^R \geq t|\mathcal{P} \text{ with training}\right] = 1 - \sum_{t^*=0}^{t-1} f_u^R(t|\mathcal{P}), \quad \forall\, t = 1, 2, ... \tag{11}$$

[19] Which basically means further integrating out (t_p, d_p, x) with respect to its observed empirical distribution.

and

$$\overline{S}_u^R(t|\mathcal{P}) = I\!P\left[T_u^R \geq t|\mathcal{P} \text{ without training}\right] = 1 - \sum_{t^*=0}^{t-1} \overline{f}_u^R(t|\mathcal{P}), \quad \forall\, t = 1, 2, ... \quad (12)$$

with $S_u^R(t|\mathcal{P})$ and $\overline{S}_u^R(t|\mathcal{P}) = 1$ for $t = 0$. Of special interest is the difference between the survival function (11) and its counterfactual (12), which following Crépon et al. (2009) may be given an interpretation in terms of average treatment effect on survival in unemployment for the treated:

$$TT_u^R(t|\mathcal{P}) = S_u^R(t|\mathcal{P}) - \overline{S}_u^R(t|\mathcal{P}) \quad (13)$$

A positive value of $TT_u^R(t|\mathcal{P})$ means that, for the considered population $\mathcal{P}$ of trainees, the probability to be still unemployed t periods after the start of their training is larger than if they actually did not get trained. Being by definition equal to zero at $t = 0$, $TT_u^R(t|\mathcal{P})$ is expected to initially increase with t, due to the fact that the trainees temporarily pass up job opportunities while in training. However, as time elapses, the trainees eventually complete their training. If training has a positive impact on the job finding rate of the trainees after the completion of their training and if this effect is large enough, then $TT_u^R(t|\mathcal{P})$ should finally turn negative. The sooner and the larger $TT_u^R(t|\mathcal{P})$ turn negative, the larger the global hopefully positive net effect of training for the considered population $\mathcal{P}$ of trainees.

5. Results

The model made of the hazard functions (1)-(2) and the unobserved individual heterogeneity distribution (3) was in practice estimated for men and women separately. The subsamples of men and women are respectively composed of 69 769 and 74 528 individuals, with a total of 88 751 and 97 100 observed spells, whose 7 193 and 7 976 respectively contain a training episode.

The estimated model is the same for both men and women. The piecewise constant baseline hazards $\lambda_u(t)$ and $\lambda_p(t)$ distinguish 11 time intervals[20]. The control variables x enclosed in $x'\beta_u$ and $x'\beta_p$ are the same and include the individual's age, level of education (3 levels), place of residence (6 sub-regions), past work experience (number of quarters in employment over the last 2.5 years), past status (employee, self-employed, other), past wage and and sector of activity (11 sectors, for employees), as well as calendar year and month dummies for controlling for yearly and seasonal effects. As already outlined, the effect of training $\delta(t|t_p, d_p, x)$ is specified as piecewise constant and allowed to vary with the starting time, duration and time elapsed since the completion of the training, as well as the type of the training and the age and education of the trainees.

The full estimation results are reported in Appendix B. We here focus on the parameters of primary interest, i.e., on the estimated parameters for the effect of training $\delta(t|t_p, d_p, x)$.

[20] The 11 time intervals are: 0-5 weeks, 6-10 weeks, 11-20 weeks, 21-30 weeks, 31-40 weeks, 41-55 weeks, 56-70 weeks, 71-90 weeks, 91-120 weeks, 121-150 weeks and more than 150 weeks.

5.1. Effect of training

The estimation results for the effect of training $\delta(t|t_p, d_p, x)$ are displayed in Table 4. They are broadly similar for men and women.

Table 4 : Effect of training

Variable	Men	Women
Time since completion of training		
Less than or equal to 2 weeks	2.063***	2.498***
	(0.066)	(0.069)
Between 3 and 13 weeks	0.666***	0.813***
	(0.066)	(0.070)
Between 14 and 39 weeks	0.646***	0.913***
	(0.065)	(0.069)
More than 39 weeks	0.776***	0.974***
	(0.067)	(0.073)
Duration of training (Ref. : between 5 and 17 weeks)		
Less than or equal to 4 weeks	-0.091**	-0.066
	(0.043)	(0.049)
More than 17 weeks	0.302***	0.282***
	(0.048)	(0.047)
Unemployment duration until training (Ref. : between 27 and 52 weeks)		
Less than or equal to 26 weeks	-0.185***	-0.259***
	(0.045)	(0.049)
More than 52 weeks	0.216***	0.096
	(0.058)	(0.063)
Type of training (Ref. : vocational)		
Non-vocational	-0.536***	-0.490***
	(0.056)	(0.051)
Age (Ref. : between 31 and 40)		
Between 25 and 30	0.016	0.034
	(0.041)	(0.045)
Between 41 and 49	0.017	-0.095*
	(0.052)	(0.051)
Education (Ref. : upper secondary)		
Primary school and lower secondary	0.099**	0.063
	(0.045)	(0.051)
Higher education	-0.210***	-0.221***
	(0.057)	(0.054)
Individuals	69 769	74 528
Unemployment spells	88 751	97 100

Note : Standard errors in parentheses. Significance level : * = 10%, ** = 5% and *** = 1%.

According to Table 4, it appears that the job finding rate of both men and women is strongly increased after the completion of their training. As a matter of fact, just after the end of their training (within the first 2 weeks), the job finding rates of men are typically[21] almost multiplied by 8 ($\approx \exp(2.063)$)[22], and afterwards

[21] i.e., for the reference case of a vocational training, starting after 27 to 52 weeks of unemployement and lasting between 5 and 17 weeks, received by an individual aged 31-40 with upper secondary education.

[22] For convenience, as argued in Section 4.1, when discussing the parameter estimates, we pretend

remain at least about 90% ($\approx \exp(0.646) - 1$) higher than it would have been without training. This typical effect is even estimated larger for women: the job finding rates of women are approximately multiplied by 12 ($\approx \exp(2.498)$) just after the end of their training, and then remain at least about 125% ($\approx \exp(0.813) - 1$) higher than without training. A similar pattern, with a comparable high increase just after training but a lower and markedly decreasing effect afterwards, was found by Richardson and van den Berg (2013) for Sweden.

The large effect just after training may to some extent result from the trainee's job search efforts during their training[23], but is most likely due to the job search assistance and professional contact network offered by the training centers. As a matter of fact, it seems for example common that employers directly contact the training centers when looking for candidates for a vacancy. The fact that the effect of training remains both substantial and persistent afterwards suggests that the initial increase of the job finding rates is not merely due to signaling and job search assistance, but also to genuine skill enhancements, resulting in better structural employment probability. Further, the fact that the effect is not only persistent but actually seems to increase somewhat as time elapsed might be due to the fact that a significant proportion – around 30% – of the trainees actually receives further training (not explicitly considered here) after their first training.

As it could be expected, longer trainings are found to have more effect on the job finding rate of both men and women than shorter trainings. Globally, a training of more than 4 months (17 weeks) is estimated to have around 45% more effect[24] than a training of at most 1 month (4 weeks).

Interestingly, the timing of entry into training also appears to matter, again for both men and women. According to Table 4, a training started after more than a year (52 weeks) of unemployment is estimated to have an effect about 45% larger[25] than a training started within the first 6 months (26 weeks) of unemployment. Note however that this larger proportional effect applies to a lower absolute hazard, due to the negative duration dependence observed in the baseline hazard of both men and women[26].

As it could also be expected, non-vocational training turns out to be less effective than vocational training, with an effect on the job finding rates of both men and women estimated approximately 40% lower[27] than for standard vocational training.

that the model was a genuine MPH model. As far as the magnitude of the effects (rather than their exact values) is concerned, it does not make any significant difference.

[23] At this respect, it is worth noting that, by definition of the data, some part of this initial effect is due to trainees which have prematurely ended their training before its planned duration because they found a job (finding a job automatically ends the training period which in our data is identifed by the period during which the trainees receive a training allowance). Although no exact figure is available, it however seems that only a small faction, most likely below 10%, of the trainess does actually not fully complete their training.

[24] More precisely, around 48% ($\approx \exp(0.302-(-0.091))-1$) for men and 42% ($\approx \exp(0.282-(-0.066))-1$) for women.

[25] More precisely, around 49% ($\approx \exp(0.216-(-0.185))-1$) for men and 43% ($\approx \exp(0.096-(-0.259))-1$) for women.

[26] See the estimated parameters of the baseline hazards reported at Table B.1 in Appendix B.

[27] More precisely, about 41% lower ($\approx \exp(-0.536) - 1$) for men and 39% lower ($\approx \exp(-0.490) - 1$) for women.

Finally, Table 4 suggests that the age of the trainees does not make much difference, except may be (slightly and unfavorably) for older women. On the other hand, the effectiveness of training appears to vary with the level of education of the trainees, for both men and women. Overall, the effect of training is found to be proportionally about 25% lower[28] for trainees with higher education than for trainees with lower education (primary school and lower secondary).

5.2. Aggregate net effect

The reference population of trainees that we considered for evaluating the net effect of training is composed of all individuals who became unemployed in 2008 and who started a training during the first 18 months (78 weeks) of their unemployment spell[29]. This way, given our January 2008 - December 2011 observation window, each of these trainees may be fully observed over 18 months from the start of their training, so that the probability distributions of their remaining unemployment duration (from training start) with and without training (6) and (7) may be estimated – using the estimated parameters of the model – over the same 78 weeks time span. As discussed in Section 4.2, these individual probability distributions may be aggregated to yield the probability distributions (9) and (10), which give the aggregated probability distributions of the remaining unemployment duration with and without training for the considered population – or some chosen subpopulation – of trainees. These aggregated probability distributions may then be compared by contrasting their median and their corresponding survival function (11) and (12).

Table 5 and Figure 3 display the results of these computations for the entire considered population of trainees. Note that the composition of this population – reported by Table A.1 in Appendix A – is essentially the same as depicted for our full sample in Table 2 and Table 3.

Table 5 : Aggregate effect of training – All trainees

Remaining unemployment from training start	With training	Without training
Probability of survival in unemployment after		
3 months (13 weeks)	85.1%	83.9%
6 months (26 weeks)	73.2%	74.9%
12 months (52 weeks)	54.8%	62.8%
18 months (78 weeks)	43.5%	55.1%
Median duration (weeks)	62	>78
Individuals	4 579	

According to Table 5, the probability that the trainees are[30] still unemployed 3 months after the start of their training is equal to 85.1%, and would have been lower and equal to 83.9% if the trainees actually did not receive any training (the

[28] More precisely, about 27% lower ($\approx \exp(-0.210-0.099))-1$) for men and 25% lower ($\approx \exp(-0.221-0.063)-1$) for women.

[29] Only the first spell of these individuals is considered.

[30] More rigorously, that a trainee drawn at random from the considered population of trainees is.

counterfactual). This is the result of the lock-in effect. However, as time elapses, more and more trainees complete their training and, as we previously found, afterwards find jobs at higher rates than without training. It turns out that 6 months after the start of their training, the trainees already have a lower probability to be still unemployed with training (73.2%) than without training (74.9%). A year and a half (18 months) after the start of their training, it appears that the trainees have almost 12 percentage points lower probability to be still unemployed with training (43.5%) than without training (55.1%).

A more detailed picture of how higher transition rates to job after training gradually compensate the lock-in effect of training is provided by Figure 3, which displays the estimated difference in survival probabilities with and without training (13) as a function of time since training start, along with a 95% confidence interval[31].

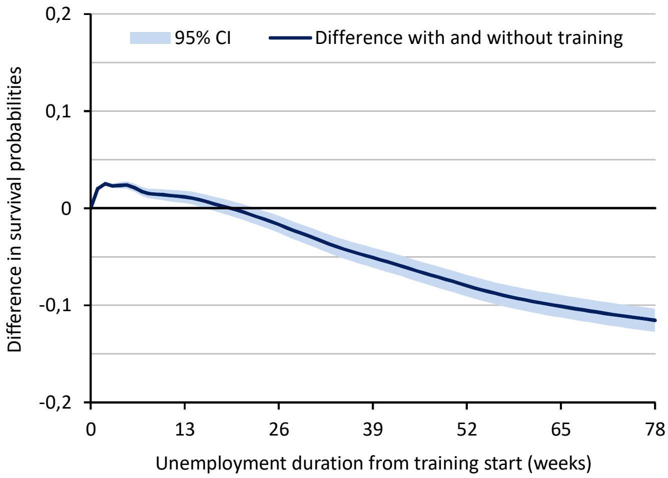

Figure 3 : Aggregate net effect of training - All trainees

As it may be seen from Figure 3, the length of the aggregate lock-in effect – i.e., the time until the probability of survival in unemployment with training becomes lower than without training – is equal to 20 weeks (around 4.5 months), and its intensity – i.e., the (maximum) value of the difference between the probabilities of survival in unemployment with and without training – does not exceed 2.5 percentage points.

A handy summary of the global net effect of training is provided by the median of the remaining unemployment duration with and without training reported in Table 5. If the trainees did not get trained, their median unemployment duration from the start of their training is estimated to have been longer than 78 weeks[32]. With training, the same median unemployment duration is estimated to 62 weeks, which means that training globally entailed a reduction of at least 16 weeks – i.e., 20.5% – of the (remaining) median unemployment duration of the trainees. This is a significant effect.

[31] The 95% confidence interval is (pointwise) obtained using the standard so-called delta method.
[32] The probability to be still unemployed has not yet decreased till 50% after 78 weeks.

Unsurprisingly, the global positive net effect of training for the overall population of trainees outlined above actually hides substantial differences across subpopulations of trainees, according to the length (short versus long), but also the type (vocational versus non-vocational), of the training that they received.

This heterogeneity is depicted by Table 6 and Table 7 which report the results of the same computations as in Table 5 above, but this time for the subpopulations of trainees who received respectively a short training – defined as a training which lasts at most 3 months – and a long training – defined as a training lasting more than 3 months –, distinguishing further in both cases the trainees who received a vocational and a non-vocational training. Corresponding analogues of Figure 3 for the different considered subpopulations are displayed in Figure 4 and Figure 5.

Table 6 : Aggregate effect of training – Short trainings ($\leq$ 3 months)

	Vocational training		Non-vocational training	
Remaining unemployment from training start	With training	Without training	With training	Without training
Probability of survival in unemployment after				
3 months (13 weeks)	71.6%	81.7%	89.6%	88.5%
6 months (26 weeks)	57.6%	71.4%	80.0%	81.4%
12 months (52 weeks)	41.5%	58.3%	67.6%	71.5%
18 months (78 weeks)	32.0%	50.0%	59.1%	64.7%
Median duration (weeks)	37	78	>78	>78
Individuals	2221		509	
Part of all trainees	48.5%		11.1%	

According to Table 6, for the trainees who received a short vocational training, it appears that the probability to be still unemployed is already (much) lower with training (71.6%) than without training (81.7%) after only 3 months from the start of their training. Further, a year and a half (18 months) after the start of their training, these trainees have 18 percentage points lower probability to be still unemployed with training (32.0%) than without training (50.0%). This (very) strong net effect is illustrated with more details in Figure 4a. From this figure, it appears that, for this subpopulation which represents the majority (48.5%) of all trainees, both the length (3 weeks) and the intensity (no more than 2.3 percentage points) of the aggregate lock-in effect is very small. This is basically due to the fact that a large part of short vocational trainings are actually very short : as reported in Table A.2 in Appendix A, their median duration is no more than 4 weeks. Overall, it is estimated that the trainees who received a short vocational training experienced a substantial reduction of 41 weeks – i.e., 52.6%, from 78 to 37 weeks – of their (remaining) median unemployment duration compared to what would have happened if they did not get trained.

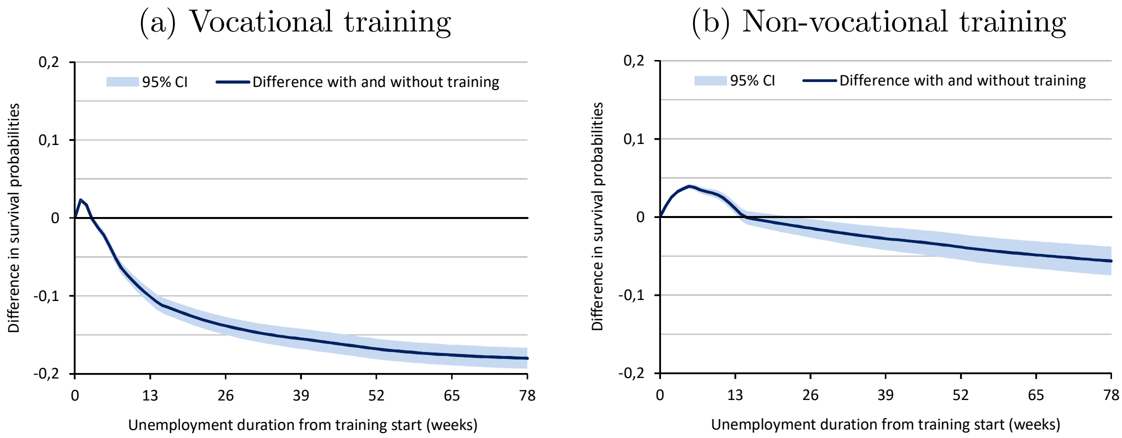

Figure 4 : Aggregate net effect of training – Short trainings (≤ 3 months)

The net effect of training is much smaller for the trainees who received a short non-vocational training. From Table 6, 3 months after the start of their training, the probability that these trainees are still unemployed is still higher with training (89.6%) than without training (88.5%). As a matter of fact, as shown by Figure 4b, for this subpopulation which represents 11.1% of all trainees, both the length (15 weeks) and the intensity (up to 3.9 percentage points) of the aggregate lock-in effect are larger than in the case of short vocational trainings. Further, the pace at which the difference in survival probabilities with and without training afterwards decreases is lower than in the case of short vocational trainings. The larger lock-in effect is partly due to the fact that, as reported in Table A.2 in Appendix A, short non-vocational trainings have a much longer median duration (8 weeks) than short vocational trainings (4 weeks). It further follows from the lower effect of non-vocational training (compared to vocational training) on the job finding rates of the trainees after training (see Table 4), the same reason explaining the lower pace at which the difference in survival probabilities afterwards decreases. Overall, the net effect of training however still finally turns moderately positive : a year and a half (18 months) after the start of their training, the trainees who received a short non-vocational training have about 5.5 percentage points lower probability to be still unemployed with training (59.1%) than without training (64.7%).

Table 7 : Aggregate effect of training – Long trainings (> 3 months)

	Vocational training		Non-vocational training	
Remaining unemployment from training start	With training	Without training	With training	Without training
Probability of survival in unemployment after				
3 months (13 weeks)	100.0%	81.5%	100.0%	88.9%
6 months (26 weeks)	86.8%	71.4%	93.2%	82.7%
12 months (52 weeks)	56.3%	58.3%	77.7%	73.0%
18 months (78 weeks)	38.9%	50.0%	66.4%	66.5%
Median duration (weeks)	60	78	>78	>78
Individuals	896		953	
Part of all trainees	19.6%		20.8%	

Although longer trainings mechanically entail larger lock-in effect, the net effect of training is still significant for the trainees who received a long vocational training. According to Table 7, for this subpopulation which represents 19.6% of all trainees, the probability to be still unemployed is still much higher with training (86.8%) than without training (73.2%) 6 months after the start of their training. As displayed by Figure 5a, the intensity of the aggregate lock-in effect actually reaches a huge 19.6 percentage points after 15 weeks – i.e., 2 weeks after the shortest training duration (13 weeks) –, but rapidly falls afterwards. The length of the aggregate lock-in effect is as long as 49 weeks (about 11 months). However, a year and a half (18 months) after the start of their training, the trainees who received a long non-vocational training actually have more than 11 percentage points lower probability to be still unemployed with training (38.9%) than without training (50.0%). This spectacular reversal is basically due to the higher effect of long vocational training (compared to shorter training) on the job finding rates of the trainees after training (see Table 4). Overall, from Table 7, it is estimated that the trainees who received a long vocational training experienced a significant reduction of at least 18 weeks – i.e., 23.1%, from 78 to 60 weeks – of their (remaining) median unemployment duration compared to what would have happened if they did not get trained.

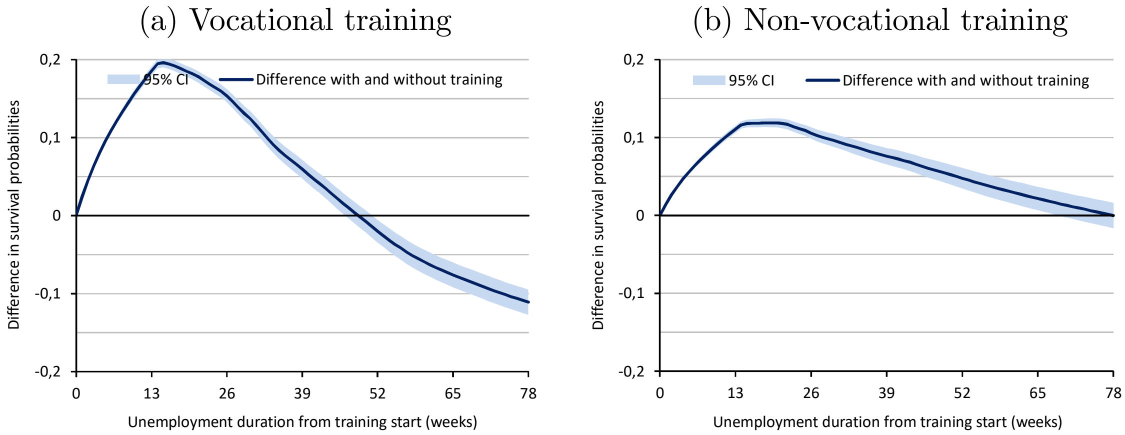

Figure 5 : Aggregate net effect of training – Long trainings (> 3 months)

As it could be expected, the net effect of training is again much lower for the trainees who received – here a long – non-vocational training. As shown by Table 7 and Figure 5b, for this subpopulation of trainees which represents 20.8% of all trainees, the initial lock-in effect is of lower intensity (at maximum equal to 11.9 percentage points after 19 weeks) than for the trainees who received a long vocational training. This follows from the fact that this subpopulation, as a result of its composition which is reported in Table A.2 of Appendix A, has lower job finding rates without training[33]. This lower initial lock-in effect is however followed by a similarly lower effect of long non-vocational training (compared to vocational training) on the job finding rates after training. Overall, it turns out that this latter effect is no longer big enough to compensate the lock-in effect, so that even a year and a half (18 months) after the start of their training, the trainees who received a long non-vocational training do not yet have a statistically significant lower probability

[33] Note that this is also true for the subpopulation of trainees who received a short non-vocational training. In that case, it likewise helps keeping low the intensity of the lock-in effect.

to be still unemployed with training (66.4%) than without training (66.5%).

To complete our evaluation of the net effect of training, Table 8 and Figure 6 contrast the (net) aggregate effect of training for the subpopulations of trainees which received, on the one hand, an early training, defined as a training that starts within the first 6 months (26 weeks) of unemployment, and on the other hand, a late training, defined as a training that starts after more than 6 months of unemployment. The median unemployment duration until training of these two subpopulations is respectively equal to 11 and 46 weeks. Otherwise, the composition of these two subpopulations – reported by Table A.3 in Appendix A –, is roughly similar.

Table 8 and Figure 6 interestingly show that trainings provided to the long-term unemployed (i.e., late trainings) globally have a larger net effect than trainings provided to the newly unemployed (i.e., early trainings).

Table 8: Aggregate effect of training – Early and late trainings (before and after 6 months of unemployment)

	Early training		Late training	
Remaining unemployment from training start	With training	Without training	With training	Without training
Probability of survival in unemployment after				
3 months (13 weeks)	82.1%	79.4%	89.4%	90.4%
6 months (26 weeks)	69.6%	69.2%	78.3%	82.9%
12 months (52 weeks)	51.0%	56.5%	60.3%	71.9%
18 months (78 weeks)	40.1%	48.6%	48.4%	64.4%
Median duration (weeks)	54	73	74	>78
Individuals	2 698		1 881	
Part of all trainees	58.9%		41.1%	

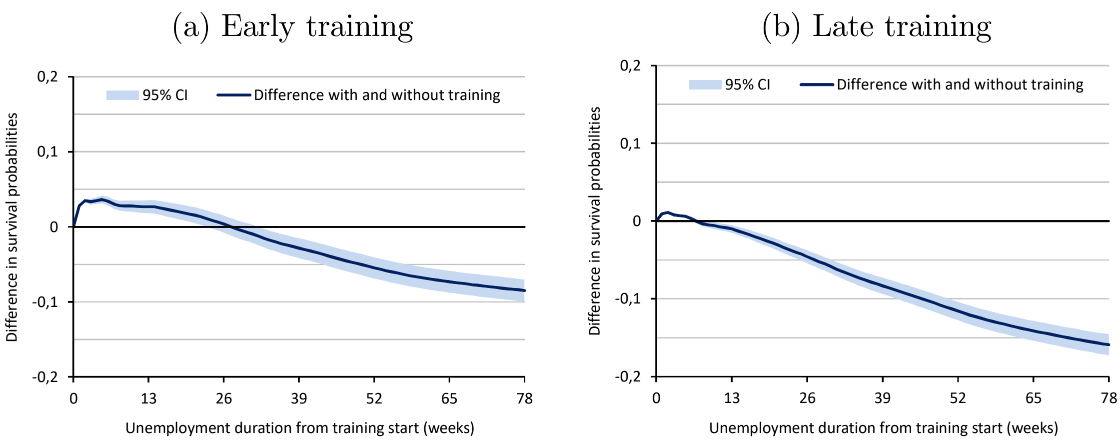

Figure 6: Aggregate net effect of training – Early and late trainings (before and after 6 months of unemployment)

As a matter of fact, from Table 8, 3 months after the start of their training, the probability that the trainees who received an early training are still unemployed is still larger with training (82.1%) than without training (79.4%), while it is already lower with training (89.4%) than without training (90.4%) for the trainees who received a late training. As displayed by Figure 6, both the length (7 weeks versus 28 weeks) and the intensity (at maximum equal to 1.1 versus 3.6 percentage points) of the aggregate lock-in effect are lower for the trainees who received a late training than for those who received an early training. Further, the pace at which the difference in survival probabilities with and without training afterwards decreases is higher in the case of late trainings. The main reasons for this are twofold. First, it follows from the fact that, due to negative duration dependence and dynamic selection, the long-term unemployed (who received late trainings) have lower job finding rates without training than the newly unemployed (who received early trainings), so that training has for the long-term unemployed a lower opportunity cost. Second, it follows from the higher relative effect of late training (compared to early training) on the job finding rates of the trainees after training (see Table 4). Overall, from Table 8, a year and a half (18 months) after the start of their training, it is estimated that the trainees who received a late training have 16 percentage points lower probability to be still unemployed with training (48.8%) than without training (64.4%), while this probability difference is no more than 8.5 percentage points (40.1% with training and 48.6% without training) for the trainees who received an early training.

6. Conclusion

The purpose of this paper was to evaluate the effectiveness of the training programs offered to the unemployed in Wallonia, the French-speaking part of Belgium. More precisely, we were interested in the two following questions : (a) does training increase the job finding rate of the unemployed after the completion of their training ? (b) if so, is this increase big enough to compensate the so-called lock-in effect of their training ? To answer these questions, we relied on the Abbring and van den Berg (2003) timing-of-events approach and a very large administrative dataset.

We found that training has an overall strong and persistent effect on the job finding rate of the unemployed after the completion of their training, but that this effect is heterogeneous : it is relatively larger just after the end of the training, for longer training, for training that starts later in the employment spell as well as for women, but lower for non-vocational training and for higher educated trainees.

Further, we also found that this effect on the job finding rate is globally large enough to compensate the lock-in effect of the training. For the overall population of trainees, we estimated that training globally entail a reduction of at least 16 weeks – i.e., 20.5% – of the median remaining time in unemployment of the trainees. This global positive net effect was however also found heterogeneous : it is the largest for the trainees who receive a short vocational training, and actually not significant for the trainees who receive a long non-vocational training, the case of the trainees who receive either a long vocational training or a short non-vocational training lying in between. Also, it is relatively larger for the long-term unemployed than for the newly unemployed.

The magnitude of the (positive) effects found in this study is somewhat higher than the one found in previous timing-of-events based studies. This might to some extent follow from the fact that our observation period is a recessionary period (after the 2008 financial crisis). According to the meta-analysis of Card et al. (2015), job training programs indeed tend to have larger impacts in such recessionary environment. This higher magnitude most likely also follows from the characteristics of the training programs offered to the unemployed in Wallonia, in particular the fact that training has a rather low participation rate (in 2011, only 6.3% of the unemployed aged 25-64 participated in a training) and that actual enrollment in a training is usually subject to a rather stringent evaluation test and/or selection/motivation interview.

To conclude, it is worth emphasizing that the present study focuses on the immediate effect of training, in terms of time spent in the current unemployment spell. Training may however be expected to also have subsequent effects in terms of employment stability (unemployment recurrence) and/or earnings, as found by Crépon et al. (2012) and Osikominu (2013) in recent timing-of-events based evaluations. This is important from a policy point of view. It implies in particular that the merits of long and/or non-vocational trainings (as opposed to short and/or vocational trainings) should not be ascertained on the only ground of their here found lower net effect on current unemployment duration.

Appendix A

This appendix contains summary statistics related to the reference population of trainees used for evaluating the aggregate net effect of training.

The composition of the entire considered population of trainees is reported in Table A.1.

Table A.1 : Reference population of trainees

Men (%)	46.0
Women (%)	54.0
Mean age (years)	34.0
Primary school and lower secondary (%)	57.8
Upper secondary (%)	25.3
Higher education (%)	16.9
Mean past employment (quarters)	4.3
Median unemployment duration until training (weeks)	20
Median duration of training (weeks)	9
Vocational training (%)	68.1
Non-vocational training (%)	31.9
Individuals	4 579

Note : Past employment is the number of quarters in employment over the last 2.5 years.

Table A.2 reports the composition of the considered population of trainees by duration (short versus long) and type (vocational versus non-vocational) of trainings.

Table A.2 : Reference population of trainees - by duration and type of trainings

	Duration and type of trainings			
	Short vocational	Short non-vocational	Long vocational	Long non-vocational
Men (%)	53.5	33.8	53.2	28.2
Women (%)	46.5	66.2	46.8	71.8
Mean age (years)	33.9	33.9	33.6	34.5
Primary school and lower secondary (%)	46.5	82.9	42.1	85.7
Upper secondary (%)	29.3	13.6	35.9	12.2
Higher education (%)	24.2	3.5	22.0	2.1
Mean past employment (quarters)	5.3	2.2	5.3	2.0
Median unemployment duration until training (weeks)	19	26	20	24
Median duration of training (weeks)	4	8	25	24
Individuals	2 221	509	896	953
Part of the reference population (%)	48.5	11.1	19.6	20.8

Note : Short trainings are trainings that last up to 3 months (13 weeks). Long trainings are trainings that last more than 3 months. Past employment is the number of quarters in employment over the last 2.5 years.

Finally, Table A.3 displays the composition of the considered population of trainees by unemployment duration until training (early versus late trainings).

Table A.3 : Reference population of trainees – by unemployment duration until training

	Early trainings	Late trainings
Men (%)	46.3	45.7
Women (%)	53.7	54.3
Mean age (years)	33.7	34.3
Primary school and lower secondary (%)	55.2	61.7
Upper secondary (%)	25.2	25.5
Higher education (%)	19.7	12.9
Mean past employment (quarters)	4.4	4.1
Median unemployment duration until training (weeks)	11	46
Median duration of training (weeks)	8	11
Short vocational training (%)	51.3	44.5
Long vocational training (%)	20.7	18.0
Short non-vocational training (%)	9.4	13.5
Long non-vocational training (%)	18.6	24.0
Individuals	2 698	1 881
Part of the reference population (%)	58.9	41.1

Note : Early trainings are trainings that start within the first 6 months (26 weeks) of unemployment. Late trainings are trainings that start after more than 6 months of unemployment. Past employment is the number of quarters in employment over the last 2.5 years. Short trainings are trainings that last up to 3 months (13 weeks). Long trainings are trainings that last more than 3 months.

Appendix B

This appendix reports the full estimation results of model (1)-(2) and (3).

Table B.1 reports the estimation results for the piecewise constant baseline hazard $\lambda_u(t)$ and the control variables x enclosed in $x'\beta_u$ of the hazard function (1), which defines the transition rates from unemployment to job. The estimation results for the effect of training $\delta(t|t_p, d_p, x)$ are displayed in Table 4 in the main text.

Table B.1 : Estimation results for the transition to job (Hazard funct. (1))

Variable	Men		Women	
Baseline hazard (Ref.: less than or equal to 5 weeks)				
Between 6 and 10 weeks	-0.367^{***}	(0.015)	-0.220^{***}	(0.015)
Between 11 and 20 weeks	-0.553^{***}	(0.016)	-0.555^{***}	(0.016)
Between 21 and 30 weeks	-0.703^{***}	(0.02)	-0.703^{***}	(0.019)
Between 31 and 40 weeks	-0.770^{***}	(0.023)	-0.815^{***}	(0.023)
Between 41 and 55 weeks	-0.856^{***}	(0.024)	-0.826^{***}	(0.023)
Between 56 and 70 weeks	-0.890^{***}	(0.028)	-0.813^{***}	(0.027)
Between 71 and 90 weeks	-0.993^{***}	(0.031)	-0.961^{***}	(0.03)
Between 91 and 120 weeks	-1.190^{***}	(0.035)	-1.083^{***}	(0.034)
Between 121 and 150 weeks	-1.448^{***}	(0.045)	-1.201^{***}	(0.043)
More than 150 weeks	-1.712^{***}	(0.058)	-1.419^{***}	(0.056)
Calendar year (Ref.: 2008)				
2009	-0.334^{***}	(0.015)	-0.209^{***}	(0.015)
2010	-0.284^{***}	(0.017)	-0.300^{***}	(0.016)
2011	-0.216^{***}	(0.02)	-0.303^{***}	(0.019)
Calendar month (Deviation from annual average)				
January	-0.004	(0.015)	0.085^{***}	(0.016)
February	-0.027^{*}	(0.015)	-0.035^{**}	(0.016)
March	0.071^{***}	(0.014)	0.017	(0.015)
April	0.104^{***}	(0.014)	0.008	(0.015)
May	0.091^{***}	(0.015)	0.006	(0.016)
June	0.059^{***}	(0.014)	-0.028^{*}	(0.015)
July	-0.353^{***}	(0.016)	-0.552^{***}	(0.017)
August	0.171^{***}	(0.013)	0.387^{***}	(0.012)
September	0.269^{***}	(0.012)	0.375^{***}	(0.012)
October	0.040^{***}	(0.014)	0.042^{***}	(0.014)
November	-0.037^{**}	(0.014)	-0.014	(0.015)
December	-0.385^{***}	(0.016)	-0.291^{***}	(0.016)
Education (Ref.: upper secondary)				
Primary school and lower secondary	-0.241^{***}	(0.014)	-0.365^{***}	(0.015)
Higher education	0.183^{***}	(0.020)	0.399^{***}	(0.017)
Age	-0.509^{***}	(0.019)	-0.342^{***}	(0.02)
Age squared	0.053	(0.059)	0.445^{***}	(0.058)
Past employment	0.870^{***}	(0.021)	1.442^{***}	(0.022)
Past employment squared	-1.501^{***}	(0.059)	-1.92^{***}	(0.06)
Age $\times$ Past employment	0.475^{***}	(0.051)	0.184^{***}	(0.05)

Table B.1 : Continuation

Type of the last job (Ref. : employee)				
Self-employed	-0.405***	(0.033)	-0.286***	(0.038)
Other	-0.065***	(0.016)	-0.121***	(0.017)
Daily earnings from the last job (for employee)	0.389***	(0.044)	0.151***	(0.044)
Daily earnings from the last job squared (for employee)	-0.337***	(0.099)	-0.156	(0.101)
Sector of activity of the last job (Ref. : agriculture, forestry and fishing, for employee)				
Mining and quarrying, manufacturing, energy, water and waste management	-0.018	(0.018)	-0.035	(0.024)
Construction	-0.090***	(0.018)	-0.288***	(0.032)
Wholesale and retail trade, repair of motor vehicles and motorcycles	-0.046***	(0.017)	-0.046***	(0.018)
Transportation and storage	0.145***	(0.023)	-0.044	(0.031)
Accomodation and food service activities	0.110***	(0.022)	0.044*	(0.023)
Information and communication, financial, insurance and real estate activities	-0.193***	(0.032)	-0.144***	(0.033)
Business services	0.162***	(0.014)	0.092***	(0.015)
Education	0.028	(0.025)	0.324***	(0.02)
Public administration, human health and social work activities	-0.265***	(0.019)	0.112***	(0.016)
Culture, sport, leisure and other services	0.026	(0.027)	0.000	(0.026)
Province of residence (Deviation from walloon average)				
Namur	0.039**	(0.015)	0.026*	(0.015)
East Hainaut	-0.104***	(0.011)	-0.170***	(0.011)
West Hainaut	0.095***	(0.017)	0.137***	(0.017)
Walloon Brabant	0.002	(0.017)	-0.037**	(0.016)
Luxembourg	-0.078***	(0.020)	0.034*	(0.019)
Liège	0.046***	(0.011)	0.010	(0.011)

Note : The variables Age, Past employment and Daily earnings are centered and divided by their range. Past employment is the number of quarters in employment over the last 2.5 years. Standard errors in parentheses. Significance level : * = 10%, ** = 5% and *** = 1%.

Table B.2 reports the estimation results for the piecewise constant baseline hazard $\lambda_p(t)$ and the control variables x enclosed in $x'\beta_p$ of the hazard function (2), which defines the access rates to training.

Table B.2 : Estimation results for the transition to training (Hazard funct. (2))

Variable	Men		Women	
Baseline hazard (Ref. : less than or equal to 5 weeks)				
Between 6 and 10 weeks	0.196***	(0.048)	0.139***	(0.044)
Between 11 and 20 weeks	0.336***	(0.044)	0.205***	(0.041)
Between 21 and 30 weeks	0.259***	(0.051)	0.040	(0.049)
Between 31 and 40 weeks	0.158***	(0.058)	-0.052	(0.055)
Between 41 and 55 weeks	0.058	(0.061)	-0.113*	(0.058)
Between 56 and 70 weeks	-0.134*	(0.072)	-0.307***	(0.068)
Between 71 and 90 weeks	-0.261***	(0.079)	-0.469***	(0.074)
Between 91 and 120 weeks	-0.510***	(0.089)	-0.743***	(0.086)
Between 121 and 150 weeks	-0.659***	(0.112)	-0.839***	(0.107)
More than 150 weeks	-1.160***	(0.160)	-1.066***	(0.139)

Table B.2 : Continuation

Calendar year (ref.: 2008)				
2009	0.058	(0.041)	0.292***	(0.040)
2010	-0.077*	(0.044)	0.126***	(0.043)
2011	-0.100*	(0.051)	0.127**	(0.050)
Calendar month (Deviation from annual average)				
January	0.340***	(0.039)	0.919***	(0.033)
February	0.364***	(0.038)	0.508***	(0.039)
March	0.329***	(0.036)	0.409***	(0.038)
April	0.052	(0.041)	0.133***	(0.042)
May	0.249***	(0.039)	0.136***	(0.044)
June	-0.077*	(0.043)	-0.321***	(0.051)
July	-1.421***	(0.080)	-2.423***	(0.133)
August	-0.261***	(0.047)	-0.388***	(0.051)
September	0.775***	(0.029)	1.238***	(0.027)
October	0.314***	(0.037)	0.467***	(0.037)
November	0.011	(0.042)	0.119***	(0.043)
December	-0.674***	(0.053)	-0.796***	(0.059)
Education (ref.: Upper secondary)				
Primary school and lower secondary	-0.247***	(0.032)	0.072**	(0.032)
Higher education	0.363***	(0.044)	0.417***	(0.041)
Age	-0.292***	(0.043)	-0.172***	(0.043)
Age squared	-0.368***	(0.134)	-0.548***	(0.136)
Past employment	0.224***	(0.048)	0.110**	(0.046)
Past employment squared	0.190	(0.137)	0.546***	(0.145)
Age × Past employment	0.420***	(0.110)	0.538***	(0.112)
Type of the last job (Ref. : employee)				
Self-employed	-0.446***	(0.082)	-0.384***	(0.101)
Other	0.009	(0.036)	0.018	(0.036)
Daily earnings from the last job(for employee)	0.047	(0.104)	0.182*	(0.106)
Daily earnings from the last job squared (for employee)	-0.089	(0.237)	-0.105	(0.254)
Sector of activity of the last job (Ref. : agriculture, forestry and fishing, for employee)				
Mining and quarrying, manufacturing, energy, water and waste management	0.179***	(0.042)	0.158***	(0.054)
Construction	-0.277***	(0.047)	-0.053	(0.069)
Wholesale and retail trade, repair of motor vehicles and motorcycles	-0.001	(0.041)	0.072*	(0.041)
Transportation and storage	0.054	(0.056)	-0.012	(0.073)
Accomodation and food service activities	-0.051	(0.057)	-0.146**	(0.058)
Information and communication, financial, insurance and real estate activities	0.045	(0.070)	0.160**	(0.073)
Business services	0.042	(0.035)	0.019	(0.036)
Education	-0.098	(0.062)	-0.439***	(0.059)
Public administration, human health and social work activities	-0.082*	(0.044)	-0.053	(0.039)
Culture, sport, leisure and other services	0.040	(0.065)	0.035	(0.062)

Table B.2 : Continuation

Province of residence (Deviation from walloon average)				
Namur	0.007	(0.035)	-0.043	(0.036)
East Hainaut	-0.085***	(0.024)	-0.162***	(0.025)
West Hainaut	0.211***	(0.038)	-0.100**	(0.042)
Walloon Brabant	-0.195***	(0.041)	-0.050	(0.038)
Luxembourg	0.081*	(0.042)	0.311***	(0.041)
Liège	-0.020	(0.024)	0.045*	(0.024)

Note : The variables Age, Past employment and Daily earnings are centered and divided by their range. Past employment is the number of quarters in employment over the last 2.5 years. Standard errors in parentheses. Significance level : * = 10%, ** = 5% and *** = 1%.

Table B.3 finally reports the estimation results for the distribution of unobserved individual effects (3), as well as some additional statistics.

Table B.3 : Estimation results for the distribution of unobserved individual effects (3)

	Men		Women	
Mass points				
v_u^1	-3.519	(0.039)	-4.094	(0.045)
v_u^2	-2.057	(0.041)	-2.611	(0.039)
v_u^3	0.664	(0.096)	-0.046	(0.099)
v_p^1	-6.441	(0.150)	-7.149	(0.230)
v_p^2	-4.398	(0.320)	-4.791	(0.350)
Joint Probabilities $I\!P[V_u = v_u, V_p = v_p]$	v_p^1	v_p^2	v_p^1	v_p^2
v_u^1	0.537	0.028	0.435	0.058
v_u^2	0.341	0.050	0.435	0.033
v_u^3	0.031	0.013	0.029	0.010
Correlation of V_u and V_p	0.199		0.016	
Test of independence of V_u and V_p				
$\chi^2(2)$ test statistic	6.529		6.110	
P-value	0.038		0.047	

Note : Standard errors in parentheses. The joint probabilities are estimated through a multinomial logit parametrization.

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