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Labour Market Transitions of French Youth

Anna Cristina D'Addio* and Michael Rosholm[‡]

Abstract

In this paper we analyse the movements of French young people between three states: employment, unemployment and non-participation, using data from the waves 1990-1992 of the French Labour Survey. Some of these event histories are left-censored. We therefore address the problem of initial conditions by invoking a stationarity assumption in the statistical framework of multi-states multi-spells duration models. We subsequently construct a Hausman test of the stationarity assumption We allow for interdependence between duration variables and we use an adjusted likelihood ratio test in order to choose the best distribution for unobservables. We are particularly interested in identifying characteristics that are associated with less favourable event histories. The results show that higher educational attainments are associated with shorter unemployment durations and with longer durations when employed. Another important factor is nationality; indeed to be of French nationality is often associated with better outcomes in the labour market.

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Keywords: event history models, left-censoring, discrete unobserved heterogeneity, youth unemployment, semi-Markov process, Hauman test, Vuong test

JEL Classification: J60, J64, C41

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1 Introduction

Youth unemployment is one of the main concerns of all governments, having implications both on the labour market and on society. It may increase the probability of future joblessness through e.g. the deterioration of individuals' skills and abilities and thereby contribute to economic exclusion and poverty. In order to identify adequate interventions and policies to reduce youth unemployment, knowledge of the ways according to which individuals move between the various states of the labour market is of considerable interest.

Various analyses have focused on the phenomenon of youth unemployment. Some authors have analyzed the impact of specific policy programs (Bonnal, Fougère and Sérandon, 1997; Werquin, 1995; Magnac 1997, Abbring, van den Berg and van Ours, 1996), others have tried to disentangle unobserved heterogeneity and state dependence (Magnac, 2000), to examine labour market conditions over a particular interval of time (Cases and Lollivier, 1994; D'Addio and Honoré, 2002). Many of the studies have been conducted in the framework of duration models. Often owing to the lack of appropriate data, only few have used event history models (Fougère and Kamionka, 1992a,c; Bonnal, Fougére and Sérandon, 1997; Magnac, 2000; D'Addio and Honoré, 2002),

This study aims at providing a detailed description of the transition patterns of young individuals - men and women - on and off the French labour market, and an identification of (combinations of) characteristics that are associated with less favourable labour market histories. In doing this we use the modelling framework developed in Rosholm (2001) modified in order to account for differences in the data. That is, we present and employ a statistical framework for event history data to describe youth mobility in and out the three states of employment (E), unemployment (U) and non-participation (N). This modelling framework is particularly useful because the likelihood function can be written in closed form, even in the presence of left-censoring and unobserved heterogeneity.

We use French Labour Force Survey data from 1990-1992 to construct the event histories of young individuals and we use these data to analyze the transitions of youth on and off the labour market.

The modelling framework allows us to account for left-censored labour market histories and thus avoids to loose a considerable amount of information that would derive by keeping only those histories that are completely observed from the "beginning". Indeed, for some persons the time of entry into the state occupied at the time of the first survey is unknown. Their trajectory is thus left-censored and a problem of initial conditions arises. This problem is solved by invoking a stationarity assumption. We subsequently derive a Hausman test which can be used to test the stationarity assumption that is rejected in our empirical application.

In order to avoid unnecessary parametric restrictions we modelled unobserved heterogeneity by following the approach of Lindsay (1983) and Heckman and Singer (1984a,b) with the number of mass-points chosen by adding points until it is no longer possible to increase the likelihood function. However since some of the mass points are not identified in the different step of the procedure, to simply compare the different likelihoods would have not been a good practice, indeed in that case the models turn out to be non-nested. For this reason and in order to choose the best specification, we used an adjusted likelihood-ratio test for non-nested model (see Vuong, 1989). Correlation between unobservables is allowed for and it generates interdependence between the different duration variables (van den Berg, 1997).

The main results can be summarized as follows. First, men and women act quite differently. This emerges clearly from both the estimated transition intensities and the different influence of the observed factors introduced in the regressions. We can notice that the transition intensities out of either employment and unemployment into non-participation are higher for women (in the same sense see Fougère and Kamionka, 1992c). Conversely it seems that employed men have higher probability of moving into unemployment than women. This higher mobility of men, may be due, for instance (as suggested in Fougère and Kamionka, 1992c), to their larger participation in the labour market through short-term contracts. Still, men show to have higher transition intensities in the $U-E$ transitions.

Second, we have noticed that unobserved heterogeneity is likely to affect strongly labour market mobility and thus to imply more or less stability of the youth on the labour market.

Finally, we have not found any evidence of negative duration dependence in the $U-E$ transitions implying both that discouragement effects are not important in the job-search process of young people and that long-term unemployment does not appear as a factor able to reduce the chances of young workers to get a job. Difficulties in achieving stability seem then linked to fixed individuals' characteristics. Hence, from a policy point of view, it could be useful to screen people flowing into unemployment to identify those having the most unfavorable characteristics. Efforts should be subsequently concentrated on those individuals by means of long-term, structural policies. In this sense, the least favorable characteristics are for both men and women low educational levels and being an immigrant. For women, being older raises detachment from the labour market.

The study is organized as follows. In the next section we briefly present some information regarding the French youth labour market. Section 3 cantains a description of the data used. The econometric model is presented in section 4, and section 5 describes parameterizations. Section 6 is devoted to a discussion of the estimation results and some specification tests, and finally some conclusions are drawn in section 7.

2 Youth labour market conditions

A number of possible explanations of high and persistent unemployment amongst the younghave been suggested in the literature: aggregate demand; youth wages; the size of the youth cohort, and lack of skills. Clearly, in finding solutions to this problem, it is crucial to determine the relative importance of these factors. As noticed by the ILO (1999), the youth labour market problem is not caused by demographic factors; the population of youth relative to the entire population of working age has been appreciably decreasing since the beginning of the seventies.

Youth labour conditions have deteriorated in almost all countries of the EU during the first half of the nineties, even if the magnitude of the effect varies from one country to the other (see Eurostat, 1997). In 1995, unemployment rates of young people were very low in Austria (5.6%) and Germany (8.8%) and very high in Finland (38.2%) and Spain (42.5%). According to the same source, in France unemployment rates of people aged less then 25 increased from 19.3% in 1990 to 27.3% in 1995. Naturally, the level of youth unemployment has instigated a debate concerning the need for structural adjustments in the labour market.

It has been argued by some authors that high rates of youth unemployment are the result of the high relative wages paid to them (Moghadam, 1993) and proposals are regularly advanced for the establishment of a (lower than the overall) youth minimum wage, like in Belgium and the Netherlands. This argument is not sufficient to explain the high rates of youth unemployment existing in France. As noticed in Bruno and Cazes (1997) France does in practice have a variety of mechanisms bringing youth wages below the level of the minimum wage (SMIC)[1]. For instance, the wages of people aged between 16 and 18 can be fixed on the basis of a floor equal to 80 per

[1] The SMIC, established in January 1970, is a gross hourly wage indexed to the consumer price index; in July of each year it is adjusted by at least half the increase in the average hourly wage, in constant Francs (Bruno and Cazes, 1997).

cent of the SMIC. Moreover, young people can be employed under "entry" contracts that enable firms to reduce their labour costs.

Generally speaking, labour market opportunities improve with the qualification level. Several studies have nevertheless shown how difficult it is for young people, whatever their educational qualifications, to achieve a rapid and direct entry into the labour market (CSERC, 1996). In particular, the overall shortage of jobs in France would tend to penalize the most recent market entrants and to place them at the back of the queue (Gautié, 1994; Bruno and Cazes, 1997). In France, the educational level of the labour force has grown continuously since the mid seventies, producing an increasingly better educated labour force. Despite this, direct entry into jobs becomes increasingly difficult for school-leavers, and the working experience of the young applicants is becoming an important factor in hiring decisions. Goux and Maurin (1993) have shown for instance that some career positions are filled more on the basis of experience consideration than on the basis of educational attainments (i.e. internal promotion of experienced workers are mainly used to fill these vacancies). Moreover, as suggested by Sneessens (1994), the unemployment of educated young people seems to be related to the mismatch between the educational system and the needs on the labour market.

The entry into professional life thus very often implies the passage through an unemployment spell; in 1995 31.1% of young unemployed persons were looking for a first job in France (Eurostat, 1997), and 23.7% of these had been unemployed for at least 12 months.

To reduce youth unemployment, or in other words to favour the entry of the young into the labour market, some new forms of first-jobs have appeared. In some countries an increasing proportion of jobs are limited term contract and temporary jobs, or jobs offered under specific policy programs. It may be that firms use these short-term labour contracts as a way to acquire information of individual productivity (Blanchard and Diamond, 1994).

3 The data

3.1 Description of the dataset and of the sample

The available data were collected by the French National Institute of Statistics (INSEE) and are extracted from the waves 1990-1992 of the French Labour Force Survey and a special survey led in 1992, called "Module Jeunes".

Data are partially retrospective in that the trajectory of the individuals in the past is rebuilt using the information collected by the interviewer at the date of the survey. With respect to the waves used in this study, interviews were carried out on three dates, in January 1990, March 1991 and March 1992. In the survey 4237 households with at least one individual aged between 18-29 belonging to them, are present at all three survey dates. The states occupied at the date of the survey and over the previous 12 months are declared at that moment, and individuals' trajectories are thus rebuilt over the period going from January 1989 to March 1992. The labour market is thus described in the dataset by a set of states through which individual can pass more than once.

The states distinguished in the survey are 1. stable employment contracts; 2. temporary employment contracts; 3. paid training; 4. unemployment; 5. schooling; 6. non-participation - including military service. To the ends of the analysis we have however merged the first three states of the survey (stable employment, temporary employment and paid training) in one aggregate state called employment (E). There are thus three mutually excluding, exhaustive states: Employment (E), Unemployment (U) and Non-Participation (N), since we only consider people that have left, or leave during the observation period, the schooling system.

The choice of these three states is based on various considerations. As to the creation of an unique state of employment, we will argue that - although the set of states that define the individual trajectory has to reflect how the labour market works (Joutard and Werquin, 1992), the high instability known by young people at the beginning of their professional life and onwards would require the use of multidimensional complex definitions covering wider and more comprehensive situations (Lechene and Magnac, 1995). However, owing to the high number of job-spells through which they pass on the labour market, it is likely that they declare some limited-term contracts as stable employment. A broader definition of employment will account for the possibility of errors in the declarations arising when individuals do not distinguish between different forms of work, for instance by confounding stable and temporary employment.

As to the definition of the other two states, we know that the borderline between unemployment and "inactivity" is not always clearly defined. Following the interpretation of Flinn and Heckman (1982a) that associate each of these two states with specific behaviour and reservation wages, we have not aggregated them in a generic state of "non-employment".

In the past many empirical studies using structural search models did not allow for this kind of transition. In reality an individual who is unemployed and actively searching for a job may drop out of the labour force at some point during unemployment (see van den Berg, 1990). For young individuals this is particularly true although the passage through inactivity (besides marriage and illness) is correlated with two different events. For young women, it is mainly associated with marriage and maternity leaves and for young men with the experience of the military service. After leaving school they are likely to know short spells of employment or unemployment and afterwards move into non-participation. Owing to the different causes of the withdrawal from the labour force, we expect different effects of the explanatory variables on the length of stay in this state. In this sense to account for this transition makes the analysis more interesting and complete.

For the empirical analysis, we have selected all the individuals that were in one of the three states listed above (E, U, N) at the beginning of the observation period (i.e. in January 1989), and those that are observed to leave the schooling system during the observation period. This results in a sample of 3182 individuals of whom 1524 are women and 1658 men. Since each individual may experience repeated spell of the same kind, we have a sample of 3504 spells for women and 3753 for men.

3.2 The variables

Official sources and empirical studies underline the difference existing in the labour market behaviour of men and women. Kaplan-Meier survival function estimates (Kaplan and Meier, 1958) for these two populations suggest that in general women have longer unemployment durations, and men have longer durations of employment. In particular, we have found evidence of strong differences in their unemployment behaviour confirmed also by a log-rank test[2] on the basis of which we reject the null hypothesis of the equality of the survivor functions. We have therefore conducted estimations separately for these two groups.

People belonging to the sample are aged between 18 and 29 in 1992; those who are on the labour market at the beginning of the observation period are thus between 16 and 26 in 1989 (i.e. 19 and 29 in 1992) as there is a minimum school-leaving age of 16 in France.

[2]This test allows comparing the survival rates of different groups. For transitions out of both employment and inactivity the null hypothesis (under which the survival rates of the groups analyzed do not differ significantly and are $\mathcal{X}^2$-distributed with $k-1$ degrees of freedom - k being the number of groups) cannot be rejected. For transitions out of unemployemnt into employment, the null hypothesis is thus rejected with a value of the test equal to 33.93. The same is true for the transitions out of unemployment into inactivity with a value of 19.67 (see Cox and Miller, 1965).

The structure of the data allows us to observe the transitions of individuals between employment, unemployment and non-participation. The numbers of transitions between those states are reported in the following tables 1 and 2 for men and women, respectively.

[Table 1 to be inserted here]

[Table 2 to be inserted here]

It can be noticed that in general young men experience more employment spells than young women. Further, while the number of unemployment and inactivity spells is similar across the two groups, inactivity spells are more often right censored for women.

In the analysis, we introduce a few explanatory variables in order to assess their influence on the mobility of young people through the three states of employment, unemployment and non-participation. Table 3 below contains some descriptive statistics for the sample.

[Table 3 to be inserted here]

The first variable included is the age of the individual as reported in 1992. It is included to capture differences in transition patterns between the very young and those a bit older. It is seen that the average age for both men and women is around 24 years, although male non-participants are on average younger.

Educational attainments are also included. They are expressed in terms of "theoretical age at end of studies", that is, the age that individuals "theoretically" should have when leaving school with a particular qualification. For instance a value of 18 of this variable implies that an individuals has left school with a "baccalauréat" (i.e. the degree allowing university entrance); it does not mean that the individual left school when 18 years old. As shown in table 3, the educational attainments of young people present in the sample are, on average, low. Indeed, only 70 women (out of 1524) and 69 men (out of 1658) have education levels higher than the "BAC", and on average women seem to be more educated than men. Many individuals in our sample have received a technical education. Crossing this variable with the previous one, we found that most males and females leave technical education with the degrees obtained (theoretically) at the age of 15 and 17.

A variable states the nationality of the father of the individual for people born in metropolitan France. It may account for the importance of the social network and, eventually, for a discrimination effect.

Using the information reported in the survey on the number of brothers and sisters the young individual has, we have built a variable stating whether the individual belongs to a large family (at least three children).

Finally, the last variable introduced in the analysis indicates whether the individual lives in Paris, and it shows that around 12% of the sample live in the capital.

In table 4, we report sum summary statistics according to the type of spells. From it, we can derive some useful information as to employability of individuals. Indeed, looking at statistics for the employment spells we can notice that individuals that begin an employment spell have relatively often a father of French nationality, they are older than in the other states and on average (especially for women) they show higher educational attainments.

4 The Model

4.1 Hazard function

The cornerstone of duration and transition models is the hazard function. In job-search theory, the hazard rate is the product of the probability of receiving a job offer in a given period and the probability that such an offer will be accepted by the unemployed person. In a reduced-form approach, the hazard rate can be modelled through the conditional probability of leaving a state explained by various factors, e.g. the time already spent in the state, the individuals' characteristics, some labour market features and other variables likely to influence the length of stay in that state. Flexible hazard functions should be preferred since they do not constrain too tightly the duration dependence parameters, and thus the baseline hazard. This general approach has been followed here to model young people transitions into and out of employment, unemployment and inactivity.

Let T_i be a continuous random variable representing duration in state i ($i = E, U, N$). The hazard rate out of a state can be interpreted as the instantaneous probability of exiting state i at time t, conditional upon survival to t (see Kiefer, 1988; Lancaster, 1990).

In a three-states model, an individual leaving a state i can enter either state j or k. The hazard function can therefore be defined as the sum of two transition functions - or destination specific hazard rates - as follows

$$h_i(t) = h_{ij}(t) + h_{ik}(t) \tag{1}$$

The destination specific hazard rate out of a particular state will depend on factors that are observed, and it is likely to be influenced also by unobserved heterogeneity. Each cause-specific hazard rate is assumed to be of the mixed proportional hazard (MPH) type. Conditional upon observed characteristics $\mathbf{x} = (\mathbf{x}_E, \mathbf{x}_U, \mathbf{x}_N)$ and unobserved characteristics $\boldsymbol{\varepsilon}= (\boldsymbol{\varepsilon}_E, \boldsymbol{\varepsilon}_U, \boldsymbol{\varepsilon}_N)$, it may be specified in the following way

$$h_{ij}(t|\mathbf{x}_i, \boldsymbol{\varepsilon}_i) = \lambda_{ij}(t)\varphi_{ij}(\mathbf{x}_i)\upsilon(\boldsymbol{\varepsilon}_{ij}) \tag{2}$$

For the baseline hazard $\lambda_{ij}(t)$, a number of specifications are available but in most cases they strongly constrain the hazard to have a specific parametric form. When left-censoring is present, a widely used baseline function is the exponential.

An important implication of this specification is the absence of duration dependence; the hazard rate is thus assumed to depend uniquely on the characteristics of the individuals and not on the length of stay in the state. This assumption can be restrictive when analysing labour market flows where duration dependence often shwos up. In job-search models positive duration dependence (in the unemployment to employment transition) may arise as a consequence of the fact that the reservation wage of an individuals tends to decrease with the length of the spell, owing for instance to the reduction of unemployment compensations or to the depreciation of the value of the leisure time. Negative duration dependence in the unemployment to employment transition may arise for instance because longer durations in unemployment are considered by employers as signals of the individual's productivity - implying that the longer an individual is unemployed, the less employable he becomes - or also owing to the appearance of discouragement effects. In the employment to unemployment/non-participation transition, it may appear since the longer a worker has been employed by a firm, the less likely he is to be fired.

To adopt an exponential transition intensity would imply ignoring these possibilities. To account for the possibility of duration dependence we have therefore decided to use a rather flexible baseline hazard, that is, the piecewise constant. This function is assumed to be constant over a specific interval, but it can vary across intervals. By increasing the number of intervals it is possible to increase the flexibility of the model.

4.2 Unobserved heterogeneity

Neglecting unobserved heterogeneity may bias the parameter estimates (e.g. see Lancaster, 1979; 1990). Moreover as a consequence, apparent negative duration dependence may arise. This is due to the so-called "mover-stayer" problem: In a sample of heterogeneous individuals, "movers" are the first to exit a state, "stayers" are thus left in the state.

In accounting for unobserved heterogeneity, we follow Heckman and Singer (1984a). Broadly speaking this amounts to approximating a distribution function of unobservables with a finite mixture distribution. This approximation is built in order to maximize sample likelihood. We estimate $\{p_i, \varepsilon_i\}_{i=1}^{W}$ where p_i is the weight placed on the unobserved components ε_i that are ordered from lowest to highest and $\sum_{i=1}^{W} p_i = 1$.

Since independence between duration variables could result in an unsatisfactory analysis of labour market mobility, we will allow for dependence between them to be generated by correlated unobserved heterogeneity components. In order to reduce the dimensionality of the unobservables' distribution, the unobservables in the two transition functions out of a given state are specified using the "one-factor loading specification". It assumes that there is a univariate random variable ε_i such that

$$\varepsilon_{ij} = \exp(\alpha_{ij} + \gamma_{ij}\varepsilon_i)$$

with i indexing the occupied state and j the destination state, and α_{ij}, γ_{ij} being parameters of the model. The consequence of this specification is to reduce the dimension of the unobservables'distribution from six to three, in the present case.

4.3 Derivation of the likelihood contribution of left and right-censored spells

The hazard rate out of a particular state i is thus assumed to be piecewise constant in each of the M intervals with splitting times $a_0, a_1, ..., a_M$. Without loss of generality we adopt the convention $a_0 = 0$ and $a_M = +\infty$ (see Lancaster, 1990). To simplify notation we suppress the dependency of the hazard on $\mathbf{x}$ and $\boldsymbol{\varepsilon}$.

Let $m(t) : \Re_+ \curvearrowright \{1, 2, ..., M\}$ be a function mapping a duration t into an interval m. We can thus write

$$h_{ij}(t) = h_{ij}^{m(t)} \tag{3}$$

where $m(t)$ is a superscript denoting the value of the transition function in the m'th interval, and

$$h_i(t) = h_i^{m(t)} = \sum_{j \neq i} h_{ij}^{m(t)} \tag{4}$$

The integrated hazard writes as

$$
\begin{aligned}
H_i(t) &= \int_0^t h_i^{m(s)} ds \\
&= \left(\sum_{m=1}^{m(t)-1} h_i^m (a_m - a_{m-1}) \right) + h_i^{m(t)} (t - a_{m(t)-1})) \\
&= H_i^{m(t)-1} + h_i^{m(t)} \left(t - a_{m(t)-1} \right)
\end{aligned}
\tag{5}
$$

where $H_i^{m(t)-1}$ is the integrated hazard up to the beginning of the m'th interval, that is, a sum of $m(t)-1$ rectangular areas.

We can derive now the contribution to the likelihood function of a single spell in state i using the fact that a right-censored observation contributes with its survivor function $1 - F_i(t) = S_i(t) = \exp[-H_i(t)]$. We define to this end d_{ij} to be an indicator for observing a transition from i to j and write the likelihood contribution for a single spell of type i as

$$
\mathcal{L}_i = \left(h_{ij}^{m(t)} \right)^{d_{ij}} \cdot \left(h_{ik}^{m(t)} \right)^{d_{ik}} \cdot \exp\left[-H_i(t) \right]
\tag{6}
$$

The contribution of a sequence of spells of various types for a single individual would then be a product of terms such as (6) above, if it were not for the complications introduced by initial conditions problems. Let us for now denote the modification to the likelihood function from the initial conditions as $\mathcal{L}_1$. Then, assuming that a person has s_e employment spells, s_u unemployment spells, and s_n non-participation spells, the likelihood contribution for a single individual, conditional on observed and unobserved variables, writes

$$
\mathcal{L}\left(\gamma; \mathbf{x}_1, \varepsilon_1, \mathbf{x}_e, \mathbf{x}_u, \mathbf{x}_n, \varepsilon_e, \varepsilon_u, \varepsilon_n \right) = \mathcal{L}_1 \cdot \prod_{k=1}^{s_e} \mathcal{L}_{e,k} \cdot \prod_{l=1}^{s_u} \mathcal{L}_{u,l} \cdot \prod_{m=1}^{s_n} \mathcal{L}_{n,m}
$$

where $\mathbf{x}_1, \varepsilon_1$ are the observed and unobserved variables, respectively, for the initial conditions.

The next two sub-sections discuss the form of $\mathcal{L}_1$. The first sub-section derives $\mathcal{L}_1$ when the event history is left-censored, that is, we know the state occupied by the individual at the beginning of the observation period, but we do not know the elapsed duration in that state, nor do we know anything else before that time. The second section, then, discusses various approaches to how to deal with persons leaving the schooling system during the observation period, that is, the transition from school into the first state occupied.

4.3.1 Left-censored labour market histories

Owing to the particular survey scheme, some observations are censored. The trajectory after March 1992 is unknown and thus it is right-censored. Similarly, it is not observed before January 1989, this implies that the trajectories of individuals that are observed at the beginning of the survey in one of the states of employment, unemployment or non-participation, are left-censored. While the first kind of censoring is routinely handled empirically, left-censoring make things more complex and rare are the attempts trying to model it empirically (see Gritz, 1993; Rosholm, 2001; D'Addio and Rosholm, 2002).

Indeed in this case one observes the length of an incomplete spell followed by a transition to one of the two destination states. The contribution of this kind of spells equals thus the probability of being observed in the initial state multiplied by the probability of the observed remaining duration in the spell. To derive the correct likelihood function one thus needs to know both the probability of being in the initial state as well as the contribution of all the spells.

In order to evaluate the probability of occupying the initial state, one has to know the inflow rate into the spell, which is a function of the elapsed duration. For left-censored spells, this information is missing and this generates the well-known "initial conditions" problem (Flinn and Heckman, 1982a,b; Heckman and Singer, 1984a,1986; Ridder, 1984). In general the problem is solved with simplifying assumptions; assuming an exponential distribution for the durations is one of them. Another solution proceeds on the parametrization of the first spell with a distribution different from that used for subsequent spells (Flinn and Heckman, 1982a; Gritz, 1993). Alternatively, one can create a flow sample of a certain kind of spells when data allow for this (see D'Addio, 1998). In our study of labour market histories, the use of a flow sample would have led to an important loss of the information available and furthermore to a highly selective sample. Finally, one can assume stationarity of the environment in order to derive the correct likelihood contribution of first spells[3]. This is the approach taken in this study. However, realizing that the assumption is critical, we also propose a Hausman test to check its validity.

In order to account for left-censoring in our analysis we have proceeded as follows. First by pointing out that we can derive the probability of being observed in state i at the time of entry into the sample by noticing that *the process described above is a continuous time semi-Markov chain.*

[3]For a survey see D'Addio (2000).

Formal definitions are given below. Second, we make particular distributional assumptions for the length of stay spent in a state, i.e. a piecewise constant hazard function, which has the properties necessary for the likelihood to be analytically derived.

A semi-Markov process is highly general from a mathematical point of view and allows for duration dependence in the rate of mobility. This process conceptually distinguishes two aspects of mobility: (1) the length of time a person spends in a given position; (2) the time-ordered sequence of positions occupied (see Tuma, 1976; Tuma et al., 1979). The process is termed semi-Markov because it is assumed to be describable by a probabilistic process that depends on a person's present position but not on his previous history. Therefore, the length a of time spent in a state (the first aspect of mobility mentioned above) may depend on characteristics of the individuals' present status and of his destination, but does not depend on the previous history. Semi-Markov processes allow representing the sequence of states entered by a Markov chain, that is, a matrix of conditional probabilities of entering a particular state after leaving an another state.

Summing up, those processes allow the transition intensities to depend on the elapsed duration but neither on calendar time, nor upon the history of the process. They appear to be particularly appealing for the modelling of labour market behaviour of individuals, which is frequently characterised by some type of duration dependence.

The probability of a transition at any time depends on how long the state has been occupied (Lancaster, 1990). If $U(\tau)$ is the state occupied at a date τ that we can define the process $\{U(\tau), \tau \geq 0\}$ to be semi-Markov if, for distinct times s_1, s_2 prior to τ, is

$$\Pr\left[U(\tau)|U(s_1), U(s_2)\right] \neq \Pr\left[U(\tau)|U(s_1)\right] \tag{7}$$

Thus, when the transition intensities depend on the elapsed duration we no longer have a Markov process (Lancaster, 1990; Fougère and Kamionka, 1992b). However, by a transformation of the time-scale, we can identify a discrete-time Markov chain embedded in the stochastic process $U(\tau)$ provided by the states occupied at the instant before each transition occurs with $\{U_n\}$ and $\{t_n\}$ denoting the sequence of states entered and the length of stay in each state at each transition n such that (see Lancaster, 1990; Florens and al. 1995; Fougère and Kamionka, 1992a; Magnac et al., 1995).

$$\begin{aligned} & \Pr\left[U_n = j|U_{n-1} = k,\right] \\ = \; & \pi_{kj}^{n} \quad n \in \mathcal{N}, j \in K, \tau \in \mathcal{R}^{+} \end{aligned}$$

To solve for initial conditions caused by the lack of information about the date of entry in the first state, time-homogenous semi-Markov processes are particularly appealing. For this kind of processes it is

$$\pi_{kj}^{n} = \pi_{kj} = \Pr\left[U_n = j | U_{n-1} = k\right]$$

that is, the transition probabilities do not depend on n, that is, on the number of transitions previously experienced by the individuals.

The discrete Markov chain U_n embedded in $U(\tau)$ has a transition probability matrix

$$\mathbf{R} = [\pi_{kj}] \tag{8}$$

with elements

$$\pi_{kj} = \begin{cases} \int_0^\infty S_k(s) h_{kj}(s) ds & \text{for } k \neq j \\ 0 & \text{for } k = j \end{cases} \tag{9}$$

where in particular it is

$$\pi_{kj} = \int_0^\infty S_k(s) h_{kj}(s) ds \tag{10}$$

It is easy to check that the CTMC (Continuous Time Markov Chain) is a special case of the semi-Markov process, arising when the duration are exponentially distributed.

Let us examine some important results about the semi-Markov process. Under some general conditions holding for the embedded Markov chain $\{U_n\}$ there exists a limiting probability distribution $\overline{\pi}$ such that (Lancaster, 1990)

$$\overline{\pi} = \overline{\pi}\mathbf{R} \tag{11}$$

Upon defining

$$\mathbf{Q} = \mathbf{R} - \mathbf{I}$$

(11) implies that there exists a unique $\overline{\pi}$ (whose elements sum to one) such that[4]

$$\overline{\pi}\mathbf{Q} = 0$$

[4]For a smart procedure of estimation of continuous time Markov chains see Kalbfleisch and Lawless (1985).

For large t the probability that the process is in state k is (Lancaster, 1990)

$$P_k = \frac{\overline{\pi}_k \mu_k}{\sum_{j=1}^{J} \overline{\pi}_j \mu_j}$$

More particularly, if we denote with $\mu_k = \int_0^\infty S_k(s)ds$ the mean duration of stay in state k, the limit distribution of the semi-Markov process $\{U(\tau)\}$ is given by

$$P_k = \lim_{\tau \to \infty} \Pr\{U(\tau) = k\} = \frac{\overline{\pi}_k \mu_k}{\sum_{j=1}^{J} \overline{\pi}_j \mu_j}$$

that expresses the probability that, for large τ, the process is in state k when observed at an arbitrary point remote from the origin.

The treatment of left-censored observations in this modelling framework proceeds on assuming that the process has been in operation for long so that the long-run probabilities can be derived (see Rosholm, 2001; D'Addio and Rosholm, 2002). We exploit this result to solve for the initial conditions problem affecting histories of people observed in one of the labour market states at the beginning of the observation period.

Taking $\mu_i = E[T_i|\mathbf{x}_i, \varepsilon_i]$, $i = e, u, n$, to be the expected value of the duration spent in a particular state conditional on the observed and unobserved heterogeneity and $\overline{\pi}_i$ the equilibrium probabilities in the embedded Markov chain we note that under appropriate assumptions concerning the beginning of the labour market process (namely, $\tau \to \infty$), the probability of being observed in state i at the starting date of the sample is then[5]

$$P_{1i} = \frac{\overline{\pi}_i \cdot E[T_i|\mathbf{x}_i, \varepsilon_i]}{\overline{\pi}_e \cdot E[T_e|\mathbf{x}_e, \varepsilon_e] + \overline{\pi}_u \cdot E[T_u|\mathbf{x}_u, \varepsilon_u] + \overline{\pi}_n \cdot E[T_n|\mathbf{x}_n, \varepsilon_n]} \tag{12}$$

In particular $E[T_i|\mathbf{x}_i, \varepsilon_i]$ is given by[6]

$$E[T_i|\mathbf{x}_i, \varepsilon_i] = \sum_{m=1}^{M} \frac{1}{h_i^m} \cdot \Pr(a_{m-1} < T_i \leq a_m|\mathbf{x}_i, \varepsilon_i) \tag{13}$$

[5] Their values are available upon request.

[6] For the derivation see Appendix A.

Left-censored observations in state i contribute to the likelihood function with the expression[7]

$$\begin{aligned}\mathcal{L}_{left,i} &= \frac{1}{E\left[T_i|\mathbf{x}_i,\varepsilon_i\right]}\cdot\left(\frac{\left(h_{ij}^{m(t)}\right)^{d_{ij}}\cdot\left(h_{ik}^{m(t)}\right)^{d_{ik}}}{h_i^{m(t)}}\right.\\ &\quad\cdot\Pr\left(t<T_i\leq a_{m(t)}|\mathbf{x}_i,\varepsilon_i\right)\\ &\quad\left.+\sum_{m=m(t)+1}^{M}\frac{\left(h_{ij}^{m}\right)^{d_{ij}}\cdot\left(h_{ik}^{m}\right)^{d_{ik}}}{h_i^{m}}\cdot\Pr\left(a_{m-1}<T_i\leq a_m|\mathbf{x}_i,\varepsilon_i\right)\right)\end{aligned}$$

The contribution of a left-censored spell to the likelihood is thus, upon defining indicators d_e and d_u for being in either employment or unemployment, respectively

$$\mathcal{L}_{1,left}=\left(P_{1e}\cdot\mathcal{L}_{left,e}\right)^{d_e}\cdot\left(P_{1u}\cdot\mathcal{L}_{left,u}\right)^{d_u}\cdot\left(P_{1n}\cdot\mathcal{L}_{left,n}\right)^{1-d_e-d_u} \tag{14}$$

4.3.2 School leavers

In our sample, some individuals leave the schooling system during the observation period. For these, there is no left-censoring problem. However, there is still an initial conditions problem, in the sense that the transition into the first state may be non-random. Hence, in the case that unobserved variables affecting the transition into the first state may be correlated with unobserved variables affecting subsequent transitions, this could lead to inconsistent parameter estimates.

There are various possibilities to the treatment of initial conditions of school leavers. A first way of proceeding is to assume a different parametrization for the distribution of the first spell (e.g. see Gritz, 1993). In this respect, a very general specification is to assume that the transition into the first spell is modelled by, for instance, a multinomial logit with inactivity being the reference state. Defining a vector of observed variables, $\mathbf{x}_1$, an unobserved variable, ε_1, and indicators d_e, d_u taking the value 1 when the first spell is employment or unemployment, respectively, we have

$$\mathcal{L}_{1,sl}=\frac{\exp\left[\left(\mathbf{x}_1\beta_e+\varepsilon_{1e}\right)d_e+\left(\mathbf{x}_1\beta_u+\varepsilon_{1u}\right)d_u\right]}{1+\exp\left[\mathbf{x}_1\beta_e+\varepsilon_{1e}\right]+\exp\left[\mathbf{x}_1\beta_u+\varepsilon_{1u}\right]}$$

where the subscript sl to the likelihood contribution means 'school leavers'.

Alternatively, we may condition on entry into the first spell(see for instance Bonnal, Fougère and Sérandon, 1997), which amounts to assuming that $\mathcal{L}_1$ is a number. For purposes of specification comparison, we specify

$$\mathcal{L}_{1,sl}=p_e^{d_e}p_u^{d_u}\left(1-p_e-p_u\right)^{1-d_e-d_u}$$

[7]For the derivation see appendix B.

where p_e, p_u denote the sample fractions of school leavers whose first spells is employment and unemployment, respectively. The advantage of this approach is that it does not imply the estimation of additional parameters, which the more general specification does.

Another possibility, which also does not require the estimation of additional parameters is to substitute one of the state occupancy or entry probabilities already in use for left-censored observation, since these depend only on already included parameters. We have tried both of these specifications, but they provide a much worse fit to the data than the conditional model specified above, hence we have discarded them.

4.3.3 The likelihood function

Let us now express the likelihood function for both left-censored histories and school-leavers. To this end, we define an indicator c, which takes the value 1 if a person is a school leaver during the observation period and 0 otherwise.

Assume that a sampled person has experienced s_e, s_u and s_n employment, unemployment and non-participation spells, respectively. Such a person will contribute to the likelihood function as follows

$$\begin{aligned} \mathcal{L}(\gamma) &= \iiiint \mathcal{L}_{1,left}^{1-c} \cdot \mathcal{L}_{1,sl}^{c} \cdot \prod_{k=1}^{s_e} \mathcal{L}_{e,k} \cdot \prod_{l=1}^{s_u} \mathcal{L}_{u,l} \cdot \prod_{m=1}^{s_n} \mathcal{L}_{n,m} \\ & \cdot g(\varepsilon_1, \varepsilon_e, \varepsilon_u, \varepsilon_n)\, d\varepsilon_1 d\varepsilon_e d\varepsilon_u d\varepsilon_n \end{aligned} \tag{15}$$

with $\varepsilon_1 = (\varepsilon_{1e}, \varepsilon_{1u})$, and $g(.,.,.,.)$ being the joint probability density function of the unobserved characteristics.

Unobserved variables are discretely distributed with W points of support and we estimate these mass points with thei associated probabilities. The likehood is the Since we have assumed heterogeneity to be a discrete distribution with a finite number of points of support the likelihood will write...

$$\mathbf{L}(\gamma) = \sum_{l=1}^{W} \mathbf{p}_l (\mathbf{L}_{1,left}^{1-c} \cdot \mathbf{L}_{1,sl}^{c} \cdot \prod_{k=1}^{s_e} \mathbf{L}_{e,k} \cdot \prod_{l=1}^{s_u} \mathbf{L}_{u,l} \cdot \prod_{m=1}^{s_n} \mathbf{L}_{n,m}) \tag{16}$$

We will exploit the fact that there are multiple spells for individuals in the sample (see Flinn and Heckman, 1982a; Honoré, 1993). This will help to identify the parameters of the distribution of unobservables. The parameters of the model will be estimated by maximizing the natural logarithm of the likelihood of the sample (that is the sum over the N individuals of the log of expression (15)).

5 Parametrization of the baseline hazard, explanatory variables and unobservables

The model described in the previous section has been separately estimated for men and women. Each cause-specific hazard $h_{ij}(.|.)$ has been defined as a function of the duration and of both observed and unobserved characteristics. It writes thus as

$$h_{ij}(t|\mathbf{x}_i, \boldsymbol{\varepsilon}_i) = \lambda_{ij}(t)\varphi_{ij}(\mathbf{x}_i)\upsilon(\varepsilon_{ij})$$

It is clear that functional form assumptions are needed.

As to baseline hazards $\lambda_{ij}(t)$ we have assumed a piecewise constant distribution for them. The splitting times have been determined both looking at the form of the empirical hazards[8] for each specific destination and origin state and accounting also for the number of transitions. This means in particular that the availability of a larger number of observations allows using more intervals. The splitting times, and thus the intervals over which the hazard is constant, are reported in the following tables 5 and 6 for men and women separately.

$[Table\ 5]$

$[Table\ 6]$

The baseline hazard $\lambda_{ij}(t)$ is parametrized as follows

$$\lambda_{ij}(t) = \exp\left(\lambda_{ij}^{m(t)}\right)$$

where $m(t)$, described in section 4, is defined in tables 5 and 6 above. In order to easily interpret the results of the baseline hazard as to the significance of duration dependence we have adopted the following identifying normalization consisting in specifying the baseline parameter vector in deviations from its value in the first interval

$$c_{ij} = \left\{\begin{array}{c} c_{ij}^1 \\ c_{ij}^2 \\ . \\ . \\ c_{ij}^k \end{array}\right\} = \left\{\begin{array}{c} 0 \\ \lambda_{ij}^2 - \lambda_{ij}^1 \\ . \\ . \\ \lambda_{ij}^{k_{ij}} - \lambda_{ij}^1 \end{array}\right\}$$

where k_{ij} is the number of different constants in the baseline hazard for the transition from i to j.

[8]Illustrations of the empirical hazards are available upon request.

Observed characteristics are accounted for in h_{ij} by means of the function $\varphi_{ij}(\mathbf{x}_i)$. One of the most used specifications to model their influence on the baseline hazard is the exponential, and this is the one we have used here. The $\varphi_{ij}(\mathbf{x}_i)$ functions are specified as

$$\varphi_{ij}(\mathbf{x}_i) = \exp(\mathbf{x}_i \boldsymbol{\beta}_{ij})$$

We turn now to the specification of unobserved heterogeneity. As previously stated, unobservables (i.e. ε_{ij}) have been assumed to follow a discrete distribution (Heckman and Singer, 1984a) with a finite number of points of support. Owing to the normalization needed for identification we define $z_{ij} = \lambda_{ij}^1 + \varepsilon_{ij}$, that has been parametrized as

$$\upsilon(\mathbf{z}_{ij}) = \exp(z_{ij})$$

Assuming that each of the z_i follows a discrete distribution with a given number, N, of points of support, the one-factor loading specification implies that the probability of observing some specific combinations of the points of support is equal to 0, that is

$$\Pr\left(z_{ij}^x, z_{ik}^y\right) \equiv \Pr\left(z_{ij}^y, z_{ik}^x\right) \equiv 0 \text{ if } x \neq y$$

Under these assumptions the distribution of unobserved heterogeneity is trivariate and the integrals in (15) is a sum of N^3 terms.

6 Results

Before turning to the analysis of the results obtained from the estimation of the models described in section 4, some considerations are in order.

By saying that the process in equilibrium, we are implicitly assuming stationarity. Since this assumption is rather restrictive, it seems necessary to construct a test for its validity. An appropriate test is the Hausman test. In order to perform it we have used the common coefficients from the "full" model estimated on a sample of students and left-censored observations and from the model estimated on the sample of school-leavers only. Under the null hypothesis of stationarity, the likelihoods (15) for the two samples are consistent and efficient. If the null fails to hold, the likelihood based on the sample of school leavers is still consistent, but inefficient. Denote the parameter vector estimated under the full likelihood by $\widehat{\psi}_{full}$ and the one obtained using only the sample of school-leavers by $\widehat{\psi}_{sl}$.

Hence, a Hausman (1978) test of the stationarity assumption may be based on

$$\mathcal{HS} = \left(\widehat{\psi}_{sl} - \widehat{\psi}_{full}\right)' \left(\widehat{V}_{sl} - \widehat{V}_{full}\right)^{-1} \left(\widehat{\psi}_{sl} - \widehat{\psi}_{full}\right) \tag{17}$$

which is asymptotically chi-squared with degrees of freedom equal to the number of parameters in ψ.

The results show that stationarity assumption is rejected in our empirical application. However, since the number of observations is really small for the sample of school-leavers, to comment the results for this group doesn't seem very useful in order to gather insights about the movement of individuals between the three states of the labour market. We have therefore decided to report the results from the full-model. On the grounds of what we said, a note of caution is in order when interpreting them.

Concerning the full model, we have estimated two models for men and women. In the first, we explicitly modelled the initial probabilities for school leavers; in the second, we conditioned on the initial states for school leavers (i.e. education). It turns out that in the former model, the variables we have used do no express much explanatory power, and therefore also the unobservables' distribution for the initial probabilities is associated with larger uncertainty. This makes it difficult to identify the distribution of unobservables, unless the observed variables have some explanatory power. Furthermore, the results from the estimation of the conditional model are practically identical to those from the more general specification. Therefore, we have chosen to report the results from the conditional model only, for ease of exposition. The estimation results from the other model are available upon request.

As mentioned in section 4, we have adopted a proportional hazard specification. Thanks to it, the coefficients are directly interpretable. A positive sign implies shorter durations in the state or, in other words, that a particular variable increases the probability of leaving the state. The converse is true for a negative sign.

As to the estimation strategy, we have started by incorporating all the explanatory variables in the hazard specification independently of the origin and of the destination state. The results showed that only some parameters were significant. In order to make computations less cumbersome and after having checked that this had no consequences (that is we have checked for correlation between variables) we decided to introduce different variables with respect to the origin and destination states. Nevertheless, variables stating the age of the individuals, their educational attainments, and the nationality of their father have been incorporated in all specifications irrespective of origin and destination.

In our model, interdependence between the duration variables is generated by the unobservables (van den Berg and Lindeboom, 1994; van den Berg, 1997). As to the unobserved heterogeneity modelling, in order to avoid unnecessary parametric restrictions, we assume that the unobserved variables are discretely distributed (Lindsay,1983), with the number of mass-points chosen by adding points until it is no longer possible to increase the likelihood function (Heckman and Singer, 1984a). However since some of the mass points are not identified in the different step of the procedure, to simply compare the different likelihoods would have not been a good practice, indeed in that case the models turn out to be non-nested. For this reason and in order to choose the best specification we used an adjusted likelihood-ratio test for non-nested model (see Vuong, 1989).

Given two conditional models F_θ and G_γ the "usual" LR test writes

$$LR_n(\widehat{\theta}_n, \widehat{\gamma}_n) = L_n^f(\widehat{\theta}_n) - L_n^g(\widehat{\gamma}_n) = \sum_{t=1}^{n} \log \frac{f(Y_t|Z_t;\widehat{\theta}_n)}{g(Y_t|Z_t;\widehat{\gamma}_n)} \tag{18}$$

where $\widehat{\theta}_n$ and $\widehat{\gamma}_n$ are the ML estimators of the pseudo-true values of θ (i.e. θ_*) and γ (i.e. γ_*) for the conditional models F_θ and G_γ; $L_n^f(\widehat{\theta}_n)$ and $L_n^g(\widehat{\gamma}_n)$ are the conditional log-likelihood functions for the model F_θ and G_γ, respectively.

Following Vuong (1989) we define the variance statistic as

$$\widehat{\omega}_n^2 = \frac{1}{n}\sum_{t=1}^{n}\left[\log \frac{f(Y_t|Z_t;\widehat{\theta}_n)}{g(Y_t|Z_t;\widehat{\gamma}_n)}\right]^2 - \left[\frac{1}{n}\sum_{t=1}^{n} \frac{f(Y_t|Z_t;\widehat{\theta}_n)}{g(Y_t|Z_t;\widehat{\gamma}_n)}\right]^2 \tag{19}$$

and we apply a correction factor defined as

$$K_n(F_\theta, G_\gamma) = (p/2)\log n - (q/2)\log n \tag{20}$$

with p and q being the degree of freedoms of the two models.

By knowing that under suitable assumptions

$$\frac{1}{n} LR_n(\widehat{\theta}_n, \widehat{\gamma}_n) \overset{a.s.}{\rightarrow} E^0\left[\log \frac{f(Y_t|Z_t;\theta_*)}{g(Y_t|Z_t;\gamma_*)}\right] \tag{21}$$

a test for non-nested model can be built and writes as

$$\widetilde{LR}_n(\widehat{\theta}_n, \widehat{\gamma}_n) = LR_n(\widehat{\theta}_n, \widehat{\gamma}_n) - K_n(F_\theta, G_\gamma) \tag{22}$$

If the two models are non-nested then

1. under $H_0 : n^{-1/2}\widetilde{LR}_n(\widehat{\theta}_n, \widehat{\gamma}_n)/\widehat{\omega}_n \overset{D}{\rightarrow} N(0,1)$

2. under $H_f : n^{-1/2}\widetilde{LR}_n(\widehat{\theta}_n, \widehat{\gamma}_n)/\widehat{\omega}_n \overset{a.s.}{\to} +\infty$,

3. under $H_g : n^{-1/2}\widetilde{LR}_n(\widehat{\theta}_n, \widehat{\gamma}_n)/\widehat{\omega}_n \overset{a.s.}{\to} -\infty$

Specifically one choose a critical value c from the standard normal distribution for some significance level (in our case 99%). If the value of the statistic $n^{-1/2}\widetilde{LR}_n(\widehat{\theta}_n, \widehat{\gamma}_n)/\widehat{\omega}_n$ is higher than c then one rejects the null hypothesis that the models are equivalent in favor of F_θ being better than G_γ. If $n^{-1/2}\widetilde{LR}_n(\widehat{\theta}_n, \widehat{\gamma}_n)/\widehat{\omega}_n$ is smaller than $-c$ then one rejects the null hypothesis that the models are equivalent in favor of G_γ being better than F_θ. Finally if $|n^{-1/2}\widetilde{LR}_n(\widehat{\theta}_n, \widehat{\gamma}_n)/\widehat{\omega}_n| \leq c$, then it is not possible to discriminate between the two competing models given the data.

By using this test in assessing the best specification of unobserved heterogeneity modelling for men and women respectively, it turns out that the preferred model for women is that with three points of support, while for men the two points of support specification is the one we retained.

In both cases as shown in tables 7, 8, 9 and 10 following, unobserved heterogeneity components are highly significant and they affect therefore the movements of young people on the labour market and this irrespective of the origin and destination states[9]. Specifically, the significance of the probabilities associated with the unobserved components suggest that there are different (with respects to the unobserved factors) groups of individuals within each sample.

[*Tables* 7, 8]

[*Tables* 9, 10]

6.1 Transitions out of unemployment

The results are reported in table 11 for men and women respectively.

[Table 11 to be inserted here]

6.1.1 Transitions out of Unemployment into Employment

Looking at the results for the transitions from unemployment into employment, we notice that in general the hazard out of unemployment into employment shows an increasing path. However this

[9]Note that in the estimations some of the probabilities approached zero. Whenever this happened the probability was set to zero (conditioned on).

appears more clearly for men rather than for women. Therefore past duration of unemployment would not reduce the opportunities of young workers of getting a job and discouragement effects are not likely to influence their job-search process. These results are compatible with the argument of a declining reservation wage which is put forward by job-search theory. However, we should be cautious in interpreting them, since a stationary assumption is implicit in our modelling strategy and it could affect our conclusions.

For the two populations analysed, higher educational attainments significantly improve the probability of finding a job. Higher levels of education seems thus an efficient way to protect individuals against the risk of experiencing long unemployment spells.

The coefficient associated with the nationality variable suggest that individuals having a father of French nationality have higher probability of finding a job, although no significant effects are found. Many studies on unemployment durations have found similar patterns associated with the individuals' nationality (see for instance Magnac, 2000). However, as we previously stated, in our analysis we use the nationality of the father and not of the individuals. Its interpretation appears to be difficult, unless one sees in it an effect of the ethnic origins of the individual, reflected for instance in his/her name or the importance of the social network in which the individual is inserted.

A strong "age effect" is found for women. Precisely, older women (in this young age group) are more likely to know longer unemployment spells and may thus experience higher difficulties to enter the labour market when compared to older men. Those have conversely (although insignificantly) higher chances to be employed. The result associated with the age of women, emerges frequently in the study of unemployment durations and shows that older women are penalised in their access to the labour market. Different causes may be at the origin of this effect; age may act as a signal of the individuals' productivity, or the reservation wage of young women may be increasing in age.

For women, the fact of living in Paris reduces unemployment duration. This effect may be linked both to labour market conditions considerations and certainly also to some kind of social rules. A big town is likely to offer more employment opportunities to women. Besides this, in small towns, and especially at the countryside, social rules are likely to be more compelling in the sense of a more traditional role of women inside the family.

6.1.2 Transitions out of Unemployment into Non-participation

Let us consider now the transition out of unemployment into non-participation.

The baseline hazards suggest again that the probability of leaving unemployment increases with the duration spent in that state. However, we cannot conclude on that since none of those parameters is significant. We also remark that there are differences in the sign of the parameters associated with age and educational attainments for men and women, while the other explanatory variables do not show up to be significant.

More precisely, younger and better educated men are more likely to move towards non-participation while the converse (that is older and less educated) is true for women. To comment these results we start by observing that besides marriage and illness, the passage through non-participation is mainly associated for these two populations with two different events. For women, the passage through this state is mainly associated with pregnancy and maternity leaves while for men it is mainly related to the experience of the military service. For this latter group, the sign associated with the education and age variables could imply that the most educated young men leave school and enter the unemployment spells in order to wait for military service. Older and less-educated men are then less likely to make this transition as they have already completed military service. For women, the converse effect implies that better qualified women are less likely to enter non-participation (in the same sense see Fougère and Kamionka, 1992c): they are probably more devoted to their careers and therefore have fewer children. Still for this population, age has certainly a direct impact on the probability of moving into non-participation. If we identify this state with pregnancy and maternity leaves, it is likely that the probability of such events increases with age.

6.2 Transitions out of employment

Baseline hazards and covariates coefficients for transitions out of employment are reported in table 12.

[Table 12 to be inserted here]

6.2.1 Transitions out of Employment into Unemployment

The baseline parameter estimates suggest a negative duration dependence in the transition out of employment into unemployment. This trend is in agreement with the theories stating that the longer a worker is employed, the lower is his/her probability to be fired. Nevertheless, we observe for both groups a slight increase in the hazard after some months. This can be explained by noticing that before being hired under a stable contract, young people often experience many short employment spells and also participate frequently in measures and programs of short duration. Therefore at the beginning of their professional life, they are likely to be very instable on the labour market and to experience high turnover rates as suggested in Jovanovic (1979).

Most explanatory variables exert a significant influence on the transitions towards unemployment. In particular, the older and the more qualified individuals turn out to be those who are less likely of loosing their jobs. The sign of the technical education coefficient shows that women having attended a technical school are likely to experience shorter employment durations. Technical education corresponds to very low educational attainments (mainly the CAP), so it may be perceived by employers as a signal of low-productivity individuals. For men, the effect of technical education is not significant, however it would suggest longer employment spells for those having acquired this kind of qualification. This results is in agreement with the one found by Moreau and Visser (1992) and D'Addio (1998).

For both men and women, the French nationality of the father is associated with the best employment chances and a significantly lower probability of experiencing unemployment. This factor seems thus to play an important role not only in the job-search process (as it shortens unemployment durations) but also while employed, leading to job-stability.

A positive effect is also found for the region-dummy variable. It seems that living in Paris also helps to achieve a greater stability on the labour market.

6.2.2 Transitions out of Employment into Non-participation

Owing to the lack of significance of the baseline parameters, we cannot definetly conclude on the presence and, eventually, on the sign on duration dependence. Nevertheless, they seem to suggest the presence of negative duration dependence that would imply that the higher the labour market attachment, the lower is the probability of entering non-participation from employment.

To comment the effect of age and educational attainments we can use the same kind of reasoning as the one used to explain the transitions from unemployment to non-participation. First, we recall to the reader that both stable and shorter employment experiences are included in the state of employment in our statistical model . Second, non-participation represents mainly the passage through two different events: the military service for men and maternity leaves for women.

For men, the effect of age and education (i.e. younger and more educated individuals make this transition more often) confirms the intuition that young men having spent more time in education, and thus having postponed the military service, are more likely to move into non-participation. Older people have normally already experienced it and the same is true for individuals that dropped out from their studies because they were normally obliged to do the military service within a very short delay. Those having chosen a technical education are conversely less likely to move into that state. By noticing again that technical education refers in our sample to very low educational attainments, the explanation for this effect seems to be coherent with the previous one.

For women we find that being younger and more educated is a clear advantage. Indeed, those having these characteristics are less likely to enter non-participation. These effects are very interesting. Human capital is expected to influence positively labour market participation. Further if we assume that it is likely to reflect the potential wage of individual, it is evident than the higher the potential wage (and therefore the education level) the higher will be the potential loss deriving from work-interruptions. From this it should follow that higher educational attainments are associated with fewer job interruptions. Looking at our results we notice that they confirm this prediction.

For men, French ethnic origins, increases the probability of entering non-participation. This effect should clearly be explained by interpreting the mobility into non-participation as mobility into the military service: this passage is indeed linked to nationality considerations.

6.3 Transitions out of Non-Participation

The results about the transitions out of non-participation are shown in table 13.

[*Table* 13]

6.3.1 Transitions out of non-participation into employment

Consider first the transitions into employment. For men, the baseline parameters show, an increasing hazard while for women it is very difficult to say something. For men, this result is compatible with the definition of the non-participation state, i.e. the probability of entering the labour market increases with the duration of the military service. Actually, this hazard rate increases dramatically after 6 months of non-participation for men. Since military service was of 12 months duration until 1992 (10 months thereafter), this may be the explanation for this extraordinary increase in the hazard rate in this interval. The sign and significance of the age and educational attainments parameters seem to be coherent with the hypothesis that this states mainly represent the passage through the military service for men.

For women age is likely to act as a productivity signal implying that older non-participants may be stigmatized. However for them, investing in education seems to play a crucial role by making it easier the entry into employment. This result is in accordance with the hypothesis of the existence of a opportunity cost for work interruptions. This cost accounts for considerations about the market wage and the present value of the reduction in the future earnings deriving from both the depreciation of the human capital associated with a work interruption and the impossibility of accumulating additional new professional experience (see Mincer and Polachek, 1974). For men, having a technical education strongly increases the probability of re-entering employment. No other variables seems to have an impact on the transition intensities governing the movement from non-participation to employment.

6.3.2 Transitions out of non-participation into unemployment

For women the sign and significance of the age coefficient confirm that older (young) women are likely to experience longer non-participation durations and are thus more vulnerable to the risk of social exclusion. For men, the coefficient associated with educational attainments, suggest that more qualified individuals are more likely to move into unemployment after a period of inactivity. This result suggests that after the military service is difficult to enter directly on the labour market and it confirms that even at higher education levels, young individuals experience nowadays increasing difficulties in achieving a stable and direct entry to it. Their labour market trajectory is very likely to begin in many cases with an unemployment spell.

7 Conclusions

In this paper we analysed the mobility of young individuals on the French labour market, between the states of employment (E), unemployment (U), and non-participation (N). Specifically, we derived the likelihood contribution of their histories in the statistical framework of multi-states, multi-spells models. To account for left-censored histories, we assumed a piecewise constant baseline hazard and thanks to its flexibility and to the long-run properties of time-homogenous semi-Markov processes, we were able to solve for the initial conditions problem. However this implies that we have implicitly invoked a stationarity assumption. In order to check for its validity, we constructed a Hausman test that rejected it in our empirical application.

Since the sample of individuals whose histories were not left-censored was really small, we have decided to present and discuss the results derived from the estimation of the “full” (conditional) model in order to give some hints about the behaviour of young people on the French labour market. This should be kept in mind in the interpretation phase since the stationarity assumption could affect our conclusions.

Nevertheless, the model we present in this study presents a considerable interest. First, it allows for accounting for those histories affected by the initial conditions problem and by there avoids to loose a considerable amount of information. Second, from a methodological point of view it seems to suggest that an effort should be made in the phase of the survey design since left-censoring is a very complex issue. Ignoring it, or using the wrong assumptions may lead to the wrong conclusions.

We also accounted for unobserved heterogeneity components (generating the interdependence between duration variables) assumed to follow a discrete distribution with a finite number of points of support (Heckman and Singer, 1984a). In order to choose the best specification for unobserved heterogeneity we performed an adjusted likelihood ratio test for non-nested models (Vuong, 1989) that allowed us to retain a three points and two points of support specification for women and men respectively.

With this study we aimed at giving a detailed description of the way young people move on the labour market, and more particularly of the factors that are likely to influence their transitions between the three states of E, U and N. Furthermore, we wanted to assess the role of unobserved heterogeneity on their mobility and to find an explicit solution to the initial conditions problem affecting the available data. These come from the waves 1990-1992 of the FLFS and make it appear that in general the position of young people on the labour market is very unstable, indeed they experience a great number of unemployment spells intersected with various employment spells.

The behaviours of young men and women seem also different according to the observed factors introduced in the analysis. In particular age is an important discriminatory factor for women (while it is not for men) penalizing their access to the labour market. Older women show thus longer unemployment durations.

Higher educational attainments are associated for both men and women with the best chances of finding and keeping a job, implying that investment in further education protects young people against emargination from the labour market.

Ethnic origins, here represented by the nationality of the young individual's father, appear to play an important role. In particular, it seems that French origins increases the chances of finding a job and of not losing it. This result should be interpreted with care in terms of a discriminatory effect. It could however reflect the importance of the social network. It is indeed likely that young individuals whose father is of French nationality have access to a larger network of information about the vacancies than foreigners.

Let us turn now to the analysis of the results linked to unobserved heterogeneity components. These show that observed factors are not sufficient to describe youth behaviour on the labour market: unobserved heterogeneity is significant and is likely then to strongly influence the movements of the youth between the three states considered.

We did not find any evidence of negative duration dependence in the $U - E$ transition allowing us to think that discouragement effects are not important in the unemployment behaviour of the young individuals present in the sample studied.

The above results can help us in deriving some conclusions.

Education seems to be the best way to protect individuals against unemployment, and more generally against excessive instability experienced on the labour market. It could be the way through which to protect the youth from social exclusion and emargination caused by the fact of being frequently unemployed. Least educated individuals should be motivated to receive additional training allowing to them to enter the labour market with higher qualification useful to compete for the available vacancies. Other policies could be oriented towards helping young people in the job-search process which is often long and difficult, especially for the youth leaving school and having no previous professional experience.

References

[1] Abbring, J.H., van den Berg, G.J. and van Ours J.C. (1996), "The Effect of Unemployment Insurance Sanctions on the Transition Rate from Unemployment to Employment", *Working Paper,* Free University of Amsterdam and Tinbergen Institute*, Amsterdam.*

[2] Blanchard, O.J. and Diamond, P. (1994), "Ranking, Unemployment Duration and Wages", *Review of economic Studies*, 61, p. 417-435

[3] Bonnal L., Fougère D. and Sérandon A. (1997) "Evaluating the Impact of French Employment Policies on Individual Labor Market Histories", *The Review of Economic Studies,* vol. 64(4), n. 221, p. 683-713.

[4] Bruno C.. and Cazes, S. (1997), "Le chômage des jeunes en France: un état des lieux", *Révue de l'OFCE*, n.62.

[5] Cases C. and Lolliver S. (1994), "Estimation d'un modèle de sortie de chômage à destinations multiples", *Economie et Prévision,* n. 113-114, p. 177-188

[6] Cox, D.R. and Miller, H.D. (1965), *The Theory of Stochastic Processes,* London, Chapman and Hall.

[7] CSERC (1996), "L'allégement des charges sociales sur les bas salaires", *La Documentation Française,* Paris.

[8] D'Addio, A.C. (1998), "Unemployment Durations of French Young People", *Discussion Paper IRES,* n. 9821, Louvain-la-Neuve, Belgium.

[9] D'Addio, A.C. (2000), *Mobility of Young People on the French Labour Market: Methodological Considerations and Empirical Analyses,* Collection des Thèses n. 360, Ph. D. Thesis, Department of Economics, Université Catholique de Louvain, Ed. Ciaco

[10] Eurostat (1997), *Les Jeunes de l'Union Européenne.*

[11] D'Addio, A.C. and B. E. Honoré (2002), "Duration Dependence and Time-Varying Variables in Discrete-Time Duration Models", mimeo.

[12] D'Addio, A.C. and M. Rosholm (2002), "Left-Censoring in Duration Data: Theory and Applications", *Working Paper* n*b*0 2002-5, Department of Economics, University of Aarhus.

[13] Flinn, C.J.and Heckman, J.J. (1982a), "Models for the Analysis of Labour Market Dynamics", in *Advances in Econometrics*, vol. 1, eds. R. Basmann, G. Rhodes, JAI Press, p. 35-95.

[14] Flinn, C.J. and Heckman J.J. (1982b), "New Methods for Analyzing Event Histories", in *Sociological Methodology,* ed. by S. Leinhardt, Jossey-Bass Publishers, San Francisco, 99-140.

[15] Florens, J.P., Fougère, D., Kamionka, T., Mouchart, M. (1995), "La modélisation économétrique des transitions individuelles sur le marché du travail", *Working Paper 9501,* Institute de Statistiques, UCL.

[16] Fougère, D. and Kamionka, Th. (1992a), "A Markovian model of the French Labour Market" (in french), *Annales d'Economie et de Statistique,* 27, pp. 149-188.

[17] Fougère, D. and Kamionka, Th. (1992b), "Individual labour market transitions" in *The Econometrics of Panel Data, Handbook of Theory and Applications*, eds. L. Matyas and P. Sevestre, Kluwer Academic Press, pp. 470-508.

[18] Fougère, D. and Kamionka, Th. (1992c), "Mobilité et précarisation sur le marché français du travail: une analyse longitudinale pour les annés 1986 à 1988", *Economie et Prévision, n. 102-103,* pp. *157-178.*

[19] Gautié, J. (1994), "Le chômage des jeunes en France: problème de formation ou de file d'attente?", *Working Paper INSEE,* n.9402.

[20] Goux, D. and Maurin, E. (1993), "Dynamique des professions et adaptation du système productif", *Economie et Statistique, n. 261.*

[21] Gritz, M. (1993), "The Impact of Training on the Frequency and the Duration of Unemployment", *Journal of Econometrics,* n.57, p. 21-51.

[22] Hausman, J. A. (1978), "Specification Tests in Econometrics", *Econometrica* vol. 46, p. 1251-1271.

[23] Heckman, J.J. and Singer, B. (1984a), "Econometric Duration Analysis", *Journal of Econometrics,* n.24, p. 63-132.

[24] Heckman, J.J., Singer, B (1984b), "A Method for Minimizing the Impact of Distributional Assumptions in Econometric Models for Duration Data", *Econometrica*, vol.52 (2), p. 271-320.

[25] Heckman, J.J., Singer, B. (1986), "Econometric Analysis of Longitudinal Data", in *Handbook of Econometrics,* vol. III, eds. Z. Griliches and M.D. Intriligator, North-Holland, Amsterdam, 1689-1763.

[26] Heckman J.J. and Walker J.R. (1990), "The relationship between wages and income and the timing and spacing of births: evidence from Swedish longitudinal data", *Econometrica*, 58, p. 1411-1441.

[27] Honoré, B. E. (1993), "Identification results for Duration Models with Multiple Spells", *Review of Economic Studies,* vol. 60, p. 241-246.

[28] ILO (1999), *Employing Youth: Promoting Employment-Incentive Growth*

[29] INSEE, *Enquête Emploi 1990, 1991, 1992.*

[30] INSEE, *Module Jeunes 1992.*

[31] Joutard, X. and Werquin, P. (1992), "Les déterminants individuels de la durée de chômage: de l'intérêt de distinguer les emplois stables des emplois précaires", *Economie et Prévision,* n.102-103, p.143-155.

[32] Jovanovic, B. (1979), "Job Matching and the Theory of Turnover", *The Journal of Political Economy,* vol. 87 (5) Part. I, pp. 972-990.

[33] Kalbfleisch, J.D. and Lawless, J.F. (1985), "The Analysis of Panel Data under a Markov assumption", *Journal of the American Statistical Association,* 80 (392), p. 863-871.

[34] Kaplan E.L. and Meier, P (1958), "Nonparametric Estimation from Incomplete Observations", *Journal of the American Statistical Association*, 53, 457-481.

[35] Kiefer, N. (1988), "Economic Duration Data and Hazard Function", *Journal of Economic Literature,* vol.26, 646-679.

[36] Lancaster, T. (1979), "Econometric Methods for the Duration of Unemployment", *Econometrica,* 47, 939-956.

[37] Lancaster, T. (1990), *The Econometric Analysis of Transition Data,* Cambridge University Press.

[38] Lechene V. and Magnac, T. (1995), "L'évaluation des politiques publiques à l'insertion des jeunes sur le marché du travail - questions microéconomiques", *Rapport à la Délégation Interministérielle à l'Insertion des Jeunes,* avril.

[39] Lindsay, B. G. (1983), "The Geometry of Mixture Likelihoods: A General Theory", *The Annals of Statistics*, vol. 11, p. 86-94.

[40] Magnac, T. (1997), "Les stages et l'insertion professionnelle des jeunes: une évaluation statistique", *Economie et Statistique,* n. 304-305, p. 75-94.

[41] Magnac, T. (2000), "Subsidized training and youth employment histories" *The Economic Journal.*

[42] Magnac, T. and Robin, J-M and Visser, M. (1995), "Analysing incomplete individual employment histories using indirect inference", *Journal of Applied Econometrics*, 10, p. 153-169.

[43] Mincer, J. and Polachek, S. (1974), "Family Investments in Human Capital: Earnings of Women" *Journal of Political Economy,* vol. 82, pp. 76-108.

[44] Moghadham, R. (1993), "Les causes de chômage en France", IMF.

[45] Moreau, A. and Visser, M. (1991), "Durées de chômage des jeunes en France", *Annales d'Economie et Statistique,* n. 20-21, p.257-278.

[46] Ridder, G. (1984), "The distribution of Single Spell Duration Data", in *Studies in Labor Market Dynamics* eds. G.R. Neumann and N.C. Westergard-Nielsen. New-York: Springer, 45-73.

[47] Rosholm, M. (2001), "An Analysis of the Processes of Labour Market Exclusion and (Re-) Inclusion" Discussion Paper 332, IZA, Bonn.

[48] Sneessens, H. (1994), "Courbe de Beveridge et demande de qualifications", *Economie et Prévision,* n. 113-114.

[49] Tuma, N.B. (1976), "Reward, resources, and the Rate of Mobility: A Nonstationary Multivariate Stochastic Model", *American Sociological Review,* vol. 41 (2), pp. 338-360.

[50] Tuma, N.B., Hannan, M.T. and Groeneveld, L.P. (1979), "Dynamic Analysis of Event Histories", *American Journal of Sociolgy,* 84, pp. 820-854.

[51] van den Berg, G.J. (1990), "Search Behaviour, Transitions to Non-Participation and the Duration of Unemployment", *The Economic Journal,* vol. 100 (402), p. 842-865.

[52] van den Berg, G.J. (1997), "Association measures for durations in bivariate hazard models", *Journal of Econometrics,* vol. 79, p 221-245.

[53] van den Berg, G.J. (1999), "Duration Models: Specifications, Identification and Multiple Durations", *Handbook of Econometrics,* vol. V, J.J Heckam and E. Lamer eds.

[54] van den Berg, G.J. and Lindeboom,M. (1994), "Heterogeneity in Models for Bivariate Survival: the Importance of the Mixing Distribution", *Journal of the Royal Statistical Society,* B 56 (1), pp. 49-60.

[55] Vuong, Q. (1989), "Likelihood Ratio Tests for Model Selection and Non-Nested Hypotheses", *Econometrica,* vol. 57(2), p. 307-333.

[56] Werquin, P. (1995), "Les dispositifs d'aide à l'insertion professionnelle des jeunes - le panel téléphonique du CEREQ", *Rapport Final,* Céreq-Dares

Appendix A: Conditional expectation of T_i

Consider[10] two duration variables with unobservables generating their interdependence. Let the hazard rate be piecewise constant. Suppose thus that the baseline is constant on each of M intervals with values $h_{i1}, .., h_{iM}$, with the splitting times $a_0, ..., a_N$, $a_0 = 0$ and $a_M = +\infty$. Let $m(t)$ be a function mapping a duration t into an interval m. The moment generating function for T_i is (where the dependency of h_i and H_i on ε_i, and h_i, H_i and the expectations on x_i is suppressed for notational convenience)

$$\begin{aligned}
\mathbf{M}_{T_i}(s|\varepsilon_i) &= \mathbf{E}\left[e^{sT_i}|\varepsilon_i\right] \\
&= \int_0^\infty e^{st} h_i^{m(t)} e^{-H_i^{m(t)-1} - h_i^{m(t)} \cdot (t - a_{m-1})} dt \\
&= \sum_{m=1}^{M} \int_{a_{m-1}}^{a_m} e^{st} h_i^m e^{-H_i^{m-1} - h_i^m (t - a_{m-1})} dt \\
&= \sum_{m=1}^{M} \frac{h_i^m}{s - h_i^m} \left(e^{sa_m - H_i^m} - e^{sa_{m-1} - H_i^{m-1}}\right)
\end{aligned} \tag{23}$$

The (conditional) expectation of T_i may easily be calculated now. First differentiate $\mathbf{M}_{T_i}(s)$ once with respect to s

$$\begin{aligned}
\mathbf{M}_{T_i}^1(s|\varepsilon_i) &= \sum_{m=1}^{M} \frac{-h_i^m}{(s - h_i^m)^2} \left(e^{sa_m - H_i^m} - e^{sa_{m-1} - H_i^{m-1}}\right) \\
&\quad + \sum_{m=1}^{M} \frac{h_i^m}{s - h_i^m} \left(a_m e^{sa_m - H_i^m} - a_{m-1} e^{sa_{m-1} - H_i^{m-1}}\right)
\end{aligned} \tag{24}$$

and evaluate this expression at $s = 0$ to find the expectation of T_i conditional on ε_i ;

$$\begin{aligned}
\mathbf{E}[T_i|\varepsilon_i] &= \sum_{m=1}^{M} \left\{ \frac{-1}{h_i^m} \left(e^{-H_i^m} - e^{-H_i^{m-1}}\right) \right. \\
&\quad \left. + \left(a_m e^{-H_i^m} - a_{m-1} e^{-H_i^{m-1}}\right) \right\} \\
&= \sum_{m=1}^{M} \frac{1}{h_i^m} \left(e^{-H_i^{m-1}} - e^{-H_i^m}\right) \\
&= \sum_{m=1}^{M} \frac{1}{h_i^m} \mathbf{P}\left(a_{m-1} < T_i \leq a_m | \varepsilon_i\right)
\end{aligned} \tag{25}$$

[10] We rely on Lancaster (1990) and Rosholm (1998).

This follows since for the second term in the first line all terms except the first and the last cancel, and these are both zero.[11]

[11] The fact that the last term ($a_M e^{-H_i^M}$) vanishes follows from the assumption that the hazard is constant in the interval $(a_{M-1}; a_M]$. The last expression can then be written as $a_M e^{-H_i^{M-1} - h_i^M (a_M - a_{M-1})}$ which is zero since $a_M = \infty$.

Appendix B: The Contribution of Left-Censored and Left- and Right-Censored Observations.

Let T_i, $i = E, U, N$, be random variable measuring the time spent in each of three states E, U, N. Assume[12] cause-specific hazard rates piecewise constant on each of M intervals with splitting times $a_0, a_1, .., a_M$, $a_0 = 0$, $a_M = +\infty$, and let $m(t)$ be a function that assigns an interval m to a given duration. Then the cause specific hazard rate can be written as

$$h_{ij}(t) = h_{ij}^{m(t)} \tag{26}$$

and

$$h_i(t) = h_i^{m(t)} = \sum_{j \neq i} h_{ij}^{m(t)} \tag{27}$$

The integrated hazard is

$$\begin{aligned} H_i(t) &= \int_0^t h_i^{m(s)} ds \\ &= \left(\sum_{m=1}^{m(t)-1} h_i^m (a_m - a_{m-1}) \right) \qquad (28) \\ &\quad + h_i^{m(t)} \left(t - a_{m(t)-1} \right) \qquad (29) \\ &= H_i^{m(t)-1} + h_i^{m(t)} \left(t - a_{m(t)-1} \right) \end{aligned}$$

such that the density of an observed duration t and destination j in state i is

$$f_i(t, j) = h_{ij}^{m(t)} \cdot \exp\left[-H_i^{m(t)-1} - h_i^{m(t)} \left(t - a_{m(t)-1} \right) \right] \tag{30}$$

and the marginal density of an observed duration t in state i is

$$f_i(t) = h_i^{m(t)} \cdot \exp\left[-H_i^{m(t)-1} - h_i^{m(t)} \left(t - a_{m(t)-1} \right) \right] \tag{31}$$

with distribution function $F_i(t)$.

[12] We rely on Lancaster (1990) and Rosholm (1998).

Now, the density of an observed elapsed duration t_e (also called a backward recurrence time) in state i is (Lancaster,1990)

$$f_{e,i}(t_e) = \frac{1 - F_i(t_e)}{\mathbf{E}[T_i]} \tag{32}$$

and the density of an observed remaining duration t_r (a forward recurrence time) conditional on the elapsed duration t_e is

$$f_{r|e,i}(t_r|t_e) = \frac{f_i(t_e + t_r)}{1 - F_i(t_e)} \tag{33}$$

Similarly, we have that the density of an observed remaining duration t_r and destination j conditional on the elapsed duration t_e is

$$f_{r,j|e,i}(t_r, j|t_e) = \frac{f_i(t_e + t_r, j)}{1 - F_i(t_e)} \tag{34}$$

and we find that the joint distributions of (t_e, t_r),and (t_e, t_r, j) are

$$\begin{aligned} f_{e,r,i}(t_e, t_r) &= \frac{f_i(t_e + t_r)}{1 - F_i(t_e)} \cdot \frac{1 - F_i(t_e)}{\mathbf{E}[T_i]} \\ &= \frac{f_i(t_e + t_r)}{\mathbf{E}[T_i]} \end{aligned} \tag{35}$$

and

$$\begin{aligned} f_{e,r,j,i}(t_e, t_r, j) &= \frac{f_i(t_e + t_r, j)}{1 - F_i(t_e)} \cdot \frac{1 - F_i(t_e)}{\mathbf{E}[T_i]} \\ &= \frac{f_i(t_e + t_r, j)}{\mathbf{E}[T_i]} \end{aligned} \tag{36}$$

respectively.

To obtain the marginal distributions of the remaining duration t_r, and (t_r, j), t_e must be integrated out of the two expressions above. We find

$$\begin{aligned} f_{r,i}(t_r) &= \int_0^\infty \frac{f_i(t_e + t_r)}{\mathbf{E}[T_i]} dt_e \\ &= \int_{t_r}^\infty \frac{f_i(s)}{\mathbf{E}[T_i]} ds \\ &= \frac{1 - F_i(t_r)}{\mathbf{E}[T_i]} \end{aligned} \tag{37}$$

and

$$
\begin{aligned}
f_{r,j,i}\left(t_r, j\right) &= \int_0^\infty \frac{f_i\left(t_e + t_r, j\right)}{\mathbf{E}\left[T_i\right]} dt_e \qquad (38)\\
&= \int_{t_r}^\infty \frac{f_i\left(s, j\right)}{\mathbf{E}\left[T_i\right]} ds \\
&= \int_{t_r}^\infty \frac{h_{ij}^{m(s)} \cdot \exp\left[-H_i\left(s\right)\right]}{\mathbf{E}\left[T_i\right]} ds \\
&= \frac{1}{\mathbf{E}\left[T_i\right]} \left(\int_{t_r}^{a_{m(t_r)}} h_{ij}^{m(t_r)} \cdot \exp\left[-H_i\left(s\right)\right] ds \right. \\
&\quad \left. + \sum_{m=m(t_r)+1}^{M} \int_{a_{m-1}}^{a_m} h_{ij}^{m} \cdot \exp\left[-H_i\left(s\right)\right] ds \right) \\
&= \frac{1}{\mathbf{E}\left[T_i\right]} \left(\frac{-h_{ij}^{m(t_r)}}{h_i^{m(t_r)}} \cdot \left(\exp\left[-H_i^{m(t_r)}\right] - \exp\left[-H_i\left(t_r\right)\right] \right) \right. \\
&\quad \left. + \sum_{m=m(t_r)+1}^{M} \frac{-h_{ij}^{m}}{h_i^{m}} \cdot \left(\exp\left[-H_i^{m}\right] - \exp\left[-H_i^{m-1}\right] \right) \right) \\
&= \frac{1}{\mathbf{E}\left[T_i\right]} \left(\frac{-h_{ij}^{m(t_r)}}{h_i^{m(t_r)}} \cdot \mathbf{P}\left(t < T_i \leq a_{m(t)}\right) \right. \\
&\quad \left. + \sum_{m=m(t_r)+1}^{M} \frac{-h_{ij}^{m}}{h_i^{m}} \cdot \mathbf{P}\left(a_{m-1} < T_i \leq a_m\right) \right) \qquad (39)
\end{aligned}
$$

The probability of a right-censored forward time is the survivor function of $f_{r,i}\left(\cdot\right)$. By going through the same steps as above, it equals

$$
\begin{aligned}
\mathbf{P}_r\left(T_i > t_r\right) &= \int_{t_r}^\infty \frac{1 - F_i\left(s\right)}{\mathbf{E}\left[T_i\right]} ds \qquad (40)\\
&= \frac{1}{\mathbf{E}\left[T_i\right]} \{ \frac{-1}{h_i^{m(t_r)}} \cdot \left(\exp\left[-H_i^{m(t_r)}\right] - \exp\left[-H_i\left(t_r\right)\right] \right) \\
&\quad + \sum_{m=m(t_r)+1}^{M} \frac{-1}{h_i^{m}} \cdot \left(\exp\left[-H_i^{m}\right] - \exp\left[-H_i^{m-1}\right] \right) \}
\end{aligned}
$$

Table 1: Descriptive statistics

Variables	MEN Mean	MEN Std. Error	WOMEN Mean	WOMEN Std. Error
Age (1)	24.1577	3.0096	25.1652	2.8235
Educational Attainments (2)	15.4527	2.1977	15.7583	2.1869
Technical Education (3)	.736744	.4404	.69178	.4618
Large family (4)	.671995	.4695	.68436	.4648
French Nationality (5)	.659472	.4739	.68949	.4627
Living in Paris (6)	.113509	.3172	.12985	.3362

(1) It is the age of individuals in 1992;
(2) This variable expresses the educational attainments in terms of "theoretical age of end of studies". Each value states the level of qualification attained by the young individual when he/she left the schooling system. it takes value in the interval [10,24], where 10 corresponds almost to a primary education level and 24 to the level of post-graduate studies;
(3) Whether the individual had a technical education. Yes=1;
(4) Whether the individual belongs to a large family, where the number of children is equal or greater than 3. Yes=1;
(5) The variables states the nationality of the individuals' father. In particular whether he is French. Yes=1;
(6) Whether the individual lives in Paris. yes=1.

Table 2: Number of transitions across the three states - Men

Origin \ Dest	E	U	N	RC	Total
E		657	232	1280	2169
U	739		77	222	1038
N	233	157		156	546
Total	972	814	309	1658	3753

E: Employment;
U: Unemployment;
N: Non-participation;
RC: Right-censoring;

Table 3 : Number of transitions across the states - Women

Dest. / Origin	E	U	N	RC	Total
E		675	186	1029	1890
U	740		83	269	1092
N	185	111		226	522
Total	925	786	269	1524	3504

Table 4 : Sub-sample descriptive statistics

Description	**Men**	**Women**
Non-Participation Spells		
Age of the individuals	22.75	25.80
Educational attainments	15.85	15.14
Technical Education %	69.41	63.41
French Nationality %	68.68	69.54
Living in Paris %	10.81	11.30
Large family %	63.55	72.8
Avg. durations of uncensored obs.	9.18	8.26
Unemployment Spells		
Age of the individuals	24.03	24.77
Educational attainments	15.19	15.55
Technical Education %	73.7	72.89
French Nationality %	60.31	64.74
Living in Paris %	9.7	10.6
Large family %	70.9	70.1
Avg. durations of uncensored obs.	5.26	7.26
Employment Spells		
Age of the individuals	24.57	25.22
Educational attainments	15.48	16.05
Technical Education %	74.73	68.62
French Nationality %	67.96	71.22
Living in Paris %	12.26	14.81
Large family %	66.34	66.24
Avg. durations of uncensored obs.	9.55	8.76

Table 5 : Splitting times for the piecewise constant hazard - Men

Type of Transition	$(0;3]$	$(3;6]$	$(6;8]$	$(8;11]$	$(11,15]$	$(15,21]$	$(21,\infty]$
$E => U$	h^1_{eu}	h^2_{eu}	h^3_{eu}	h^4_{eu}	h^5_{eu}	h^6_{eu}	h^7_{eu}
$E => N$	h^1_{en}			h^2_{en}			h^3_{en}
$U => E$	h^1_{ue}	h^2_{ue}	h^3_{ue}		h^4_{ue}	h^5_{ue}	h^6_{ue}
$U => N$	h^1_{un}		h^2_{un}		h^3_{un}		
$N => E$	h^1_{ne}	h^2_{ne}	h^3_{ne}				
$N => U$	h^1_{nu}						

Table 6 : Splitting time for the piecewise constant hazard - Women

Type of Transition	$(0;3]$	$(3;6]$	$(6;8]$	$(8;11]$	$(11,15]$	$(15,21]$	$(21,\infty]$
$E => U$	h^1_{eu}	h^2_{eu}	h^3_{eu}	h^4_{eu}	h^5_{eu}	h^6_{eu}	h^7_{eu}
$E => N$	h^1_{en}			h^2_{en}			h^3_{en}
$U => E$	h^1_{ue}	h^2_{ue}	h^3_{ue}		h^4_{ue}	h^5_{ue}	h^6_{ue}
$U => N$	h^1_{un}		h^2_{un}		h^3_{un}		
$N => E$	h^1_{ne}	h^2_{ne}	h^3_{ne}		h^4_{ne}		
$N => U$	h^1_{nu}				h^2_{nu}		

Table 7: Unobserved heterogeneity components - Men [13]

$N \to E$		
Z_1	-2.8509**	(0.2707)
Z_2	-30	–

$N \to U$		
Z_1	-4.1844**	(0.3007)
Z_2	-2.7545**	(0.2633)

$U \to E$		
Z_1	-3.6193**	(0.1529)
Z_2	-1.6724**	(0.1125)

$U \to N$		
Z_1	-5.3815**	(0.4168)
Z_2	-6.0388**	(0.5218)

$E \to U$		
Z_1	-2.3023**	(0.1614)
Z_2	-4.3645**	(0.2105)

$E \to N$		
Z_1	-5.1138**	(0.2955)
Z_2	-5.0968**	(0.2054)

[13] Standard errors in parentheses.

**Significant at 2%; *Significant at 5%.

Table 8 :Unobserved heterogenenity components - Women [14]

$N \rightarrow E$

Z_1	-4.357**	(1.1178)
Z_2	-1.9406**	(0.4226)
Z_3	-4.7372**	(0.2595)

$N \rightarrow U$

Z_1	-2.5715**	(0.4804)
Z_2	-4.0779**	(0.4546)
Z_3	-5.5418**	(0.9519)

$U \rightarrow E$

Z_1	-4.0025**	(0.3484)
Z_2	-2.7794**	(0.2373)
Z_3	-1.7129**	(0.1112)

$U \rightarrow N$

Z_1	-4.6696**	(0.4445)
Z_2	-5.6391**	(0.9166)
Z_3	-5.6919**	(0.4025)

$E \rightarrow U$

Z_1	-2.4271**	(0.162)
Z_2	-4.3842**	(0.2522)
Z_3	-4.2839**	(0.1176)

$E \rightarrow N$

Z_1	-4.6356**	(0.273)
Z_2	-2.7277**	(0.4294)
Z_3	-5.6093**	(0.3064)

Table 9: Parameters of the unobservables distribution - Men

$P(z_{u1}, z_{e_1}, z_{n_1})$	0	–
$P(z_{u1}, z_{e1}, z_{n_2})$	0.1129**	(0.0131)
$P(z_{u1}, z_{e_2}, z_{n_1})$	0.3004**	(0.0241)
$P(z_{u1}, z_{e2}, z_{n2})$	0	–
$P(z_{u2}, z_{e_1}, z_{n_1})$	0.1457**	(0.0209)
$P(z_{u2}, z_{e_1}, z_{n2})$	0	–
$P(z_{u2}, z_{e_2}, z_{n_1})$	0.2805**	(0.0384)
$P(z_{u2}, z_{e2}, z_{n2})$	0.1605**	(0.0295)

[14]Standard errors in parentheses.

**Significant at 2%; *Significant at 5%.

Table 10: Parameters of the unobservables distribution - Women [15]

$P(z_{u1}, z_{e_1}, z_{n_1})$	0	–
$P(z_{u1}, z_{e1}, z_{n_2})$	0	–
$P(z_{u1}, z_{e1}, z_{n_3})$	0	–
$P(z_{u1}, z_{e_2}, z_{n_1})$	0	–
$P(z_{u1}, z_{e2}, z_{n2})$	0.0479**	(0.0178)
$P(z_{u1}, z_{e_2}, z_{n_3})$	0.1195**	(0.0357)
$P(z_{u1}, z_{e_3}, z_{n_1})$	0	0
$P(z_{u1}, z_{e_3}, z_{n_2})$	0	0
$P(z_{u1}, z_{e3}, z_{n_3})$	0.18**	(0.0752)
$P(z_{u2}, z_{e_1}, z_{n_1})$	0.1217**	(0.0391)
$P(z_{u2}, z_{e_1}, z_{n2})$	0	–
$P(z_{u2}, z_{e1}, z_{n_3})$	0.051	(0.0419)
$P(z_{u2}, z_{e_2}, z_{n_1})$	0	–
$P(z_{u2}, z_{e2}, z_{n2})$	0	–
$P(z_{u2}, z_{e_2}, z_{n_3})$	0	–
$P(z_{u2}, z_{e_3}, z_{n_1})$	0.1424	(0.0848)
$P(z_{u2}, z_{e_3}, z_{n_2})$	0.256**	(0.083)
$P(z_{u2}, z_{e3}, z_{n_3})$	0	–
$P(z_{u2}, z_{e_1}, z_{n_1})$	0	–
$P(z_{u2}, z_{e_1}, z_{n2})$	0.0642**	(0.024)
$P(z_{u2}, z_{e1}, z_{n_3})$	0	–
$P(z_{u2}, z_{e_2}, z_{n_1})$	0	–
$P(z_{u2}, z_{e2}, z_{n2})$	0	–
$P(z_{u2}, z_{e_2}, z_{n_3})$	0	–
$P(z_{u2}, z_{e_3}, z_{n_1})$	0	–
$P(z_{u2}, z_{e_3}, z_{n_2})$	0	–
$P(z_{u2}, z_{e3}, z_{n_3})$	0.017	(0.0591)

[15]Standard errors in parentheses.

**Significant at 2%; *Significant at 5%.

Table 11 : Transitions out of Unemployment [16]

	Men		Women	
	Coefficients		Coefficients	
$U \rightarrow E$				
γ_2^{ue}	0.547**	(0.0996)	0.4792**	(0.1399)
γ_3^{ue}	0.4449**	(0.1174)	0.2295	(0.1813)
γ_4^{ue}	0.8506**	(0.1971)	0.6356**	(0.2398)
γ_5^{ue}	1.0757**	(0.2556)	0.3161	(0.2666)
γ_6^{ue}	1.2952**	(0.2244)	0.5142	(0.6260)
Age in 1992	0.0041	(0.0139)	-0.0525**	(0.0196)
Educational attainments	0.0814**	(0.0181)	0.1346**	(0.0284)
Technical education$_{1=Yes}$	-0.0369	(0.0865)	-0.0623	(0.1131)
Living in Paris$_{1=Yes}$	-0.0338	(0.1197)	0.405**	(0.1593)
Father's nationality$_{1=French}$	0.087	(0.0682)	0.1305	(0.1051)
$U \rightarrow N$				
γ_2^{un}	0.4436	(0.3468)	0.3456	(0.3109)
γ_3^{un}	0.557	(0.403)	0.6746	(0.7455)
Age in 1992	-0.3315**	(0.0613)	0.2055**	(0.0564)
Educational attainments	0.2683**	(0.0789)	-0.1514**	(0.0639)
Technical education$_{1=Yes}$	0.4701	(0.318)	-0.2001	(0.2560)
Father's nationality$_{1=French}$	0.4688*	(0.2441)	0.283	(0.2661)

[16]Standard errors in parentheses.

**Significant at 2%; *Significant at 5%.

Table 12: Transitions out of Employment [17]

	Men		Women	
	Coefficients		Coefficients	
$E \rightarrow U$				
γ_2^{eu}	0.073	(0.1316)	0.2701	(0.1735)
γ_3^{eu}	-0.3892	(0.2152)	0.0221	(0.1697)
γ_4^{eu}	-0.0726	(0.1565)	-0.1284	(0.1763)
γ_5^{eu}	-0.7087**	(0.2258)	0.1568	(0.2441)
γ_6^{eu}	-0.5933**	(0.2074)	-0.557**	(0.1918)
γ_7^{eu}	-0.7896**	(0.1782)	-0.9718*	(0.4737)
Age in 1992	-0.0751**	(0.018)	-0.05126**	(0.0192)
Educational attainments	-0.0982**	(0.0261)	-0.10693**	(0.0241)
Technical education$_{1=Yes}$	-0.0594	(0.0995)	0.2987**	(0.1042)
Living in Paris$_{1=Yes}$	-0.4704**	(0.1951)	-0.2118*	(0.1154)
Father's nationality$_{1=French}$	-0.2771**	(0.0964)	-0.3405**	(0.1068)
Large Family$_{1=Yes}$	0.1569	(0.1073)	0.1115	(0.0996)
E–N				
γ_2^{en}	-0.5045*	(0.2483)	-0.4876	(0.3081)
γ_3^{en}	-0.1887	(0.1719)	-0.6936	(0.5237)
Age in 1992	-0.3236**	(0.0275)	0.1046	(0.0361)
Educational attainments	0.1374**	(0.0331)	-0.2195**	(0.0497)
Technical education$_{1=Yes}$	-0.3116*	(0.1479)	-0.1698	(0.1758)
Living in Paris$_{1=Yes}$	-0.4325*	(0.2335)	-0.4834*	(0.2693)
Father's nationality$_{1=French}$	0.3777**	(0.1478)	-0.1319	(0.1988)

[17] Standard errors in parentheses.

**Significant at 2%; *Significant at 5%.

Table 13: Transitions out of Non-Participation

	Men		Women	
	Coefficients		Coefficients	
$N \rightarrow E$				
γ_2^{ne}	-0.6266**	(0.2748)	0.6358**	(0.2959)
γ_3^{ne}	0.7141**	(0.2004)	0.4009	(0.2152)
Age in 1992	0.2879**	(0.0343)	-0.1584**	(0.0383)
Educational attainments	-0.2414**	(0.0394)	0.2897**	(0.0600)
Technical education$_{1=yes}$	0.7134**	(0.1937)	0.0133	(0.2077)
Father's nationality$_{1=French}$	0.1442	(0.1515)	0.1825	(0.2334)
Large Family$_{1=Yes}$	-0.109	(0.1552)	-0.2943	(0.2189)
$N \rightarrow U$				
Age in 1992	-0.0681	(0.0434)	-0.17284**	(0.0476)
Educational attainments	0.0852**	(0.0401)	0.04619	(0.0729)
Technical education$_{1=Yes}$	0.0357	(0.2075)	0.3491	(0.3079)
Father's nationality$_{1=French}$	-0.2578	(0.2005)	0.2172	(0.2928)

[17]Standard errors in parentheses.

**Significant at 2%; *Significant at 5%.

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