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Evaluating the Impact of French Employment Policies on Individual Labour Market Histories

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This paper deals with the evaluation of some public employment policies set up in France during the 1980's to improve the labour market prospects of unskilled young workers. The evaluation implemented in this paper is restricted to the impact of such public measures on durations and outcomes of subsequent spells of unemployment and employment. The econometric study is conducted with non-experimental longitudinal microdata recording individual labour market histories. A particular attention is paid to the differential effects of various types of measures, according to the educational level of recipients. Programmes involving a higher level of on-the-job training, such as alternating work/training programmes in private firms, are principally beneficial to the less educated young workers. In contrast, for more educated young workers, "work fare" programmes in the public sector decrease the intensity of transition from the subsequent unemployment spell to regular jobs; for that subgroup, "work fare" programmes may act as a signal of low employment performance.

I. INTRODUCTION

This paper deals with the evaluation of public employment policies set up in France during the 1980's to improve the labour market prospects of the most disadvantaged and unskilled young workers. This evaluation, however, is restricted to the impact of youth employment schemes on subsequent unemployment and employment durations of recipients. For that purpose, we estimate a reduced-form multi-state multi-spell transition model that includes participation in these programmes as an additional state. In this framework, participation in a programme (or "training") is allowed to affect the transition rates out of the state that follows the programme, and distinct types of programmes (namely, programmes in the public sector vs. programmes in the private sector) are allowed to have differential effects. Moreover, our model allows for possibly related unobserved heterogeneity in the specifications of all transition rates, thus capturing the potentially selective nature of training enrolment. The empirical analysis makes use of non-experimental longitudinal micro data collected by INSEE (Institut National de la Statistique et des Etudes Economiques, Paris) from 1986 to 1988. These data are based on administrative records supplemented by a series of four interviews over one and a half years; they provide information on the dates of entry into training programmes and on durations of subsequent spells of employment and unemployment.

Our paper is directly connected with previous studies estimating effects of programme participation by using individual transition data (see, for example, Ridder (1986), Card and Sullivan (1988), Ham and Lalonde (1990, 1996), Gritz (1993)). Three types of motivation justify this approach:

- firstly, for disadvantaged or unskilled groups of workers, it seems more natural to focus on re-employment rates rather than on earnings gains for which empirical evidence is less clear (see Bassi (1983) or Ashenfelter and Card (1985), for example); moreover, because public employment programmes are directed at individuals, they have to be evaluated at the individual level, with the use of longitudinal micro data;
- secondly, there is an obvious interest in estimating separately the effects of programmes on subsequent durations of unemployment and employment; Ham and Lalonde (1996, p. 176) point out that separating these effects allows the comparison of different programmes: for example, "policy makers may prefer to fund a programme that lengthens employment durations as opposed to one that shortens unemployment durations, because the former is likely to lead to more stable job histories and greater human capital accumulation"; moreover, estimating the two kinds of effects is necessary to evaluate the long-run impact of these programmes. These considerations are particularly well adapted to the situation of the French labour market, which was characterized during the last fifteen years by the coexistence of different public employment programmes, long-term employment contracts (roughly speaking, "regular jobs") and short-term employment contracts (roughly speaking, "temporary jobs");
- finally, the main advantage of individual labour market transition data is that they include multiple spells per respondent; it is well known that, in the mixed proportional hazard (MPH) model for single-spell duration data, the identification of unobserved heterogeneity and duration dependence relies crucially on the multiplicative nature of the transition rate (see Elbers and Ridder (1982) and Ridder (1990)); more recently, Honoré (1993) has shown that this identification result is still valid in MPH multi-spell models without lagged duration dependence, under rather general assumptions on the joint distribution of the unobserved heterogeneity terms; this identifiability argument shows that it is very well possible to deal with the endogeneity of programme participation and to obtain reliable training effect evaluations with non-experimental continuous-time transition data.[1]

Papers by Ridder (1986) and Gritz (1993) are the most important previous studies examining the effects of programme participation on labour market histories with the use of non-experimental transition data. Our paper differs from them in several aspects. For example, Ridder (1986) does not control for unobserved heterogeneity; moreover, he considers that the selection of programme participants is an exogenous process, only affected by the labour force state reached just before entering the programme. Obviously,

1. It has been argued that, in order to be able to evaluate the effects of training programmes, it is necessary to have data from a social or natural experiment. However, contributions by Heckman and Hotz (1989), Heckman (1990), Dubin and Rivers (1993) and Ham and Lalonde (1996) emphasize the potential biases inherent in experimental studies: generally, random assignment does not eliminate all biases due to endogenous selection, especially in multi-stage training programmes. This limitation reduces the prior advantage of experimental data.

this last assumption is inappropriate: the selection is generally made by programme administrators, but also by employers participating in the programme (or offering jobs subsidized through this programme), and finally by workers themselves, who either accept or refuse offers to participate. Our empirical analysis is much more comparable with the study made by Gritz (1993). Like Gritz, we treat participation in a programme as a separate (possibly recurrent) state of a continuous labour market transition process, and we allow entry rates into programmes to depend on an unobserved individual random covariate which is possibly correlated with unobserved heterogeneity terms affecting rates of transition to other states. Moreover, when estimating the effects of programme participation on the transition rates out of the state which follows the programme, we distinguish between the effects of different types of programmes (essentially, programmes in the public sector vs. programmes in the private sector). However, contrary to Gritz, we stratify the sample with respect to the educational level and so we can produce empirical evidence on the beneficial effects of "on-the-job" training programmes for the less educated young workers. A time-varying covariate indicating qualification to receive unemployment insurance benefits through the unemployment spell is also introduced, and we study the sensitivity of parameter estimates to assumptions concerning the distribution of the unobserved heterogeneity components. Finally, our statistical modelling attempts to reduce the endogenous stock sampling bias due to the fact that the respondents are drawn from the stock of individuals who were unemployed at a particular date. It also takes into account the attrition bias due to endogenous exits from the panel. To correct such biases, we apply the methodology recently introduced by Van den Berg, Lindeboom and Ridder (1994).

Table 1.1 presents the main features of youth training programmes which were in effect in France during the late 1980's. Most of these programmes were launched before, but the numbers of participants increased greatly after the 1986 Emergency Plan for Youth Employment ("Plan d'Urgence pour l'Emploi des Jeunes"). This Plan introduced strong incentives for private firms offering training places (see Table 1.1) and facilitated the development of programmes with alternating spells of work and training ("formations en alternance", for which we propose the term "alternating work/training programmes"). For instance, the lower age limit for entry into such programmes has been lowered from 18 to 16 years, while the upper age limit for entry into the apprenticeship system has been raised from 20 to 25 years. To simplify, we can distinguish between two types of programmes: the alternating work/training programme provided by private firms (including apprenticeship, qualification and adaptation contracts, and "courses for preparation to the working life"; see Table 1.1), and the "workfare" programme provided by the State and the public sector (including community jobs and "courses for the 16-to-25 years old"; see Table 1.1). In this second type of programme, the amount of vocational and specific training is generally lower than in the first type. Then the main question we address in this paper is the following: can we also differentiate these two types of programme when we consider their impacts on durations and outcomes of subsequent unemployment and employment spells? Results show that these impacts depend crucially on the initial educational level of trainees. Programmes involving a higher level of on-the-job training, such as alternating work/training programmes in private firms, are principally beneficial to the less educated young workers, who may increase their human capital and work experience through these programmes. In contrast, for more educated young workers, "workfare" programmes in the public sector decrease the intensity of transition from the subsequent unemployment spell to regular jobs; for that subgroup, "workfare" programmes may act as a signal of low employment performance.

Section II gives some descriptive statistics on the sample. Section III presents the transition model and the likelihood function we estimate. Results are commented upon in Section IV. Our conclusions are summarized in the last section.

TABLE 1.1

Summary table of main programmes for youth employment in France during the period 1986–1988

Programmes	Durations	Objectives	Eligible workers	Potential employers	Amount of training	Wage levels	Employer incentives
Apprenticeship contracts	Temporary employment contracts (between 1 and 3 years)	To provide a specific training giving a formal qualification or allowing to take examination for national diploma after completion	Young people without any diploma or without any formal qualification	All private firms in craft, trade and industrial sectors	At least 400 hours of training for non-college graduates; at least 1500 hours of training for college graduates	The apprentice is paid by the firm, the wage depends on age and seniority in the contract (between 17 and 75% of the legal minimum wage)	Firms are exempted from paying social security contributions
Qualification contracts	Temporary employment contracts (between 6 and 24 months)	Idem	Idem	All private firms	At least one quarter of the contract duration	Idem	Firms are exempted from paying social security contributions and the employer training tax
Adaptation contracts	Either temporary employment contracts (from 6 to 12 months) or permanent employment contracts	To provide a specific training (adapted to the job occupied)	Young people with a formal qualification but who have difficulties to find a job	Idem	At least 200 hours in the case of a temporary contract; for permanent employment contracts, it depends both on the job and on the young worker's qualification	The wage is paid by the firm; it is at least equal to the legal minimum wage	Firms are exempted from paying the employer training tax but have to pay social security contributions (since July 1987)
Courses for preparation to the working life (SIVP)	Non-renewable temporary contracts	To give a formal qualification (adapted to existing jobs)	Young people with no work experience or unemployed for more than one year	Idem	Training provided either by the firm or by a government training centre	Trainees receive a lump-sum from the state and a complementary allowance from the firm	Firms are exempted from paying social security contributions
Community jobs (TUC)	Non-renewable temporary employment contracts (from 3 to 12 months or 24 months since 1987)	To help young people to find a regular job	Young workers between 16 and 21 years old or long term unemployed between 22 and 25 years old	State or local administration, public institutions, non-profit making associations, . . .	No formal or specific training	Trainees are paid by the state and receive a fixed payment (about 1250FF) and sometimes an allowance from the firm	
Training courses for 16 to 25 years-old	Courses with a duration between 6 and 9 months	To facilitate social and professional integration	Young people leaving the educational system without any qualification	Courses take place in state training centres	Between 550 and 700 hours of training	Trainees receive a lump-sum from the state	

II. THE DATA

The data used for this study are provided by the "Suivi des Chômeurs" survey collected by INSEE (Paris). The sample was drawn randomly in August 1986 from the files of the public employment service ("Agence Nationale Pour l'Emploi" or ANPE).[2] About 8000 unemployed people were sampled but only 7450 could be reached at the first interview. Individuals were interviewed four times, in November 1986, May 1987, November 1987, and finally May 1988. At the first interview, respondents were asked to give information on their labour market status between August and November 1986, and in particular on the time already spent in the unemployment spell sampled in August 1986 and on their status before entry into that spell. The data record retrospectively month after month, between November 1986 and May 1988, the events corresponding to individual transitions in the labour market. For that study, we consider only young men who were less than 26 years old in August 1986 and for whom it is possible to observe an accurate and relevant date of registration in the ANPE files. Table 2.1 gives descriptive statistics for this sub-sample which contains 1337 individuals.

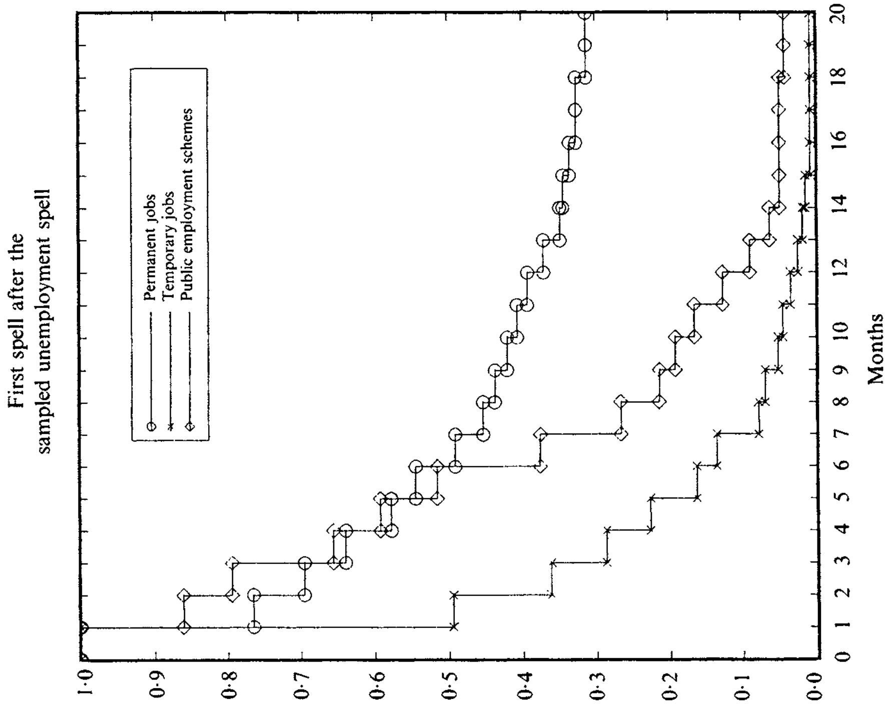
TABLE 2.1

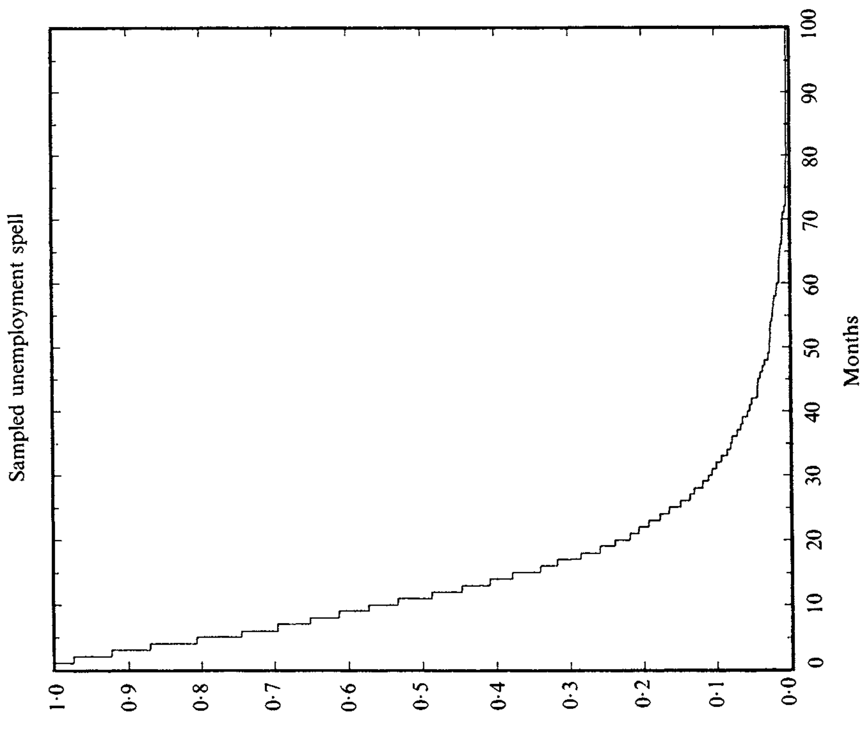
Descriptive statistics

Variables	Min	Max	Mean	Standard deviation
French nationality	0	1	0·9289	
Age in November 1986	15	26	21·17	2·66
Skill level				
Unskilled blue-collar worker	0	1	0·5086	
Skilled blue-collar worker	0	1	0·2094	
White-collar worker	0	1	0·1810	
Other levels	0	1	0·1010	
Educational level				
No diploma	0	1	0·5033	
Technical school certificate	0	1	0·3029	
High school diploma and above	0	1	0·092	
Non-response	0	1	0·1017	
Reason of entry into the sampled unemployment spell				
End of a temporary employment contract	0	1	0·3119	
Lay-off	0	1	0·1511	
Quit	0	1	0·2034	
First entry (including after military service)	0	1	0·3336	
Individual characteristics in August 1986				
Qualification for UI	0	1	0·25	
Previous participation to a programme	0	1	0·16	
Duration of the sampled unemployment spell (without right-censored spells)	1	79	13·36	11·67

Figure 2.2 presents Kaplan–Meier estimates for survival functions of durations in successive spells (without correction of the stock-sampling bias). These curves show that, during the first year of occupation, the exit rate from training programmes is lower than the exit rate from temporary jobs: for instance, in the first spell observed after the sampled unemployment spell, the mean duration of a programme is about four months while the mean duration of a temporary job is approximately three months. The exit rates from

2. These files include all unemployed people registered at the ANPE who were looking either for a full-time or part-time permanent job, or a full-time or part-time temporary job in August 1986. These requirements do not correspond to the definition of unemployment given by the International Labour Office.


First spell after the
sampled unemployment spell
Permanent jobs
Temporary jobs
Public employment schemes
Months


Sampled unemployment spell
Months

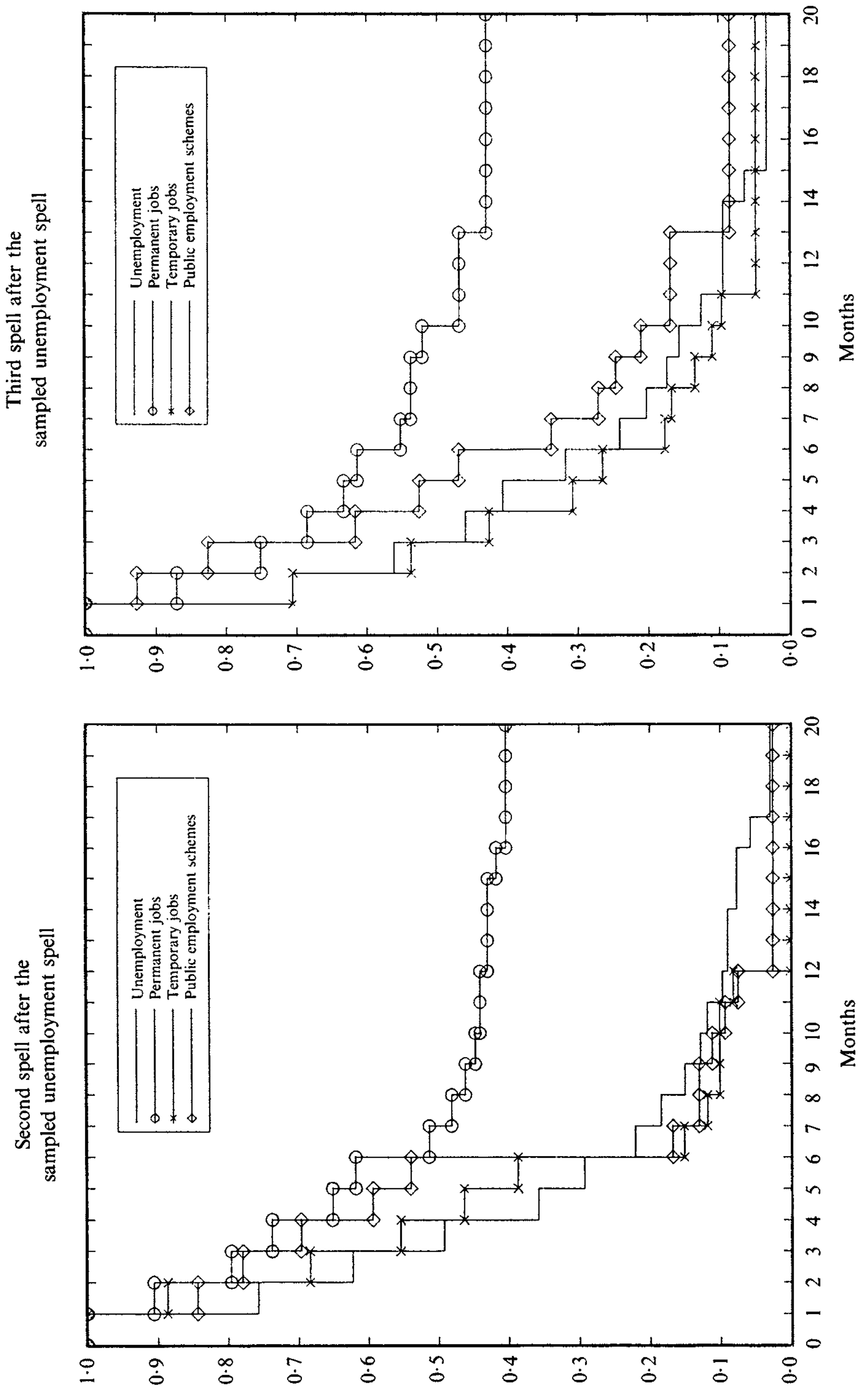


FIGURE 2.2

Kaplan–Meier estimates of survival functions of durations in successive spells unemployment spells occurring after the second observed spell are higher than the exit rate from the initial unemployment spell: this could be due either to a heterogeneity bias (long-term vs. recurrent unemployment) or to the small length of the observation period. This last problem could also affect the results, because some of the programmes being evaluated have durations that are potentially longer than the sampling frame (e.g. the apprenticeship programme includes contracts of up to three years).

Figure 2.3 gives a general description of the transitions experienced by the young male subsample between August 1986 and May 1988. In this figure, we consider three employment states: permanent employment (UDC), temporary employment (LDC), and employment resulting from a public employment policy (PEP). Because of the small numbers of corresponding transitions, we do not make any distinction between the different kinds of public employment policies, such as TUC, SIVP, "qualification" or "adaptation" contracts, ... described in the introduction. Moreover, besides the usual states of unemployment (U) and out-of-labour-force (OLF), we treat the phenomenon of attrition as a particular state of the transition process. Individuals who leave the panel through attrition do not re-enter the sample at following interviews. Consequently, attrition (A) is an absorbing state.

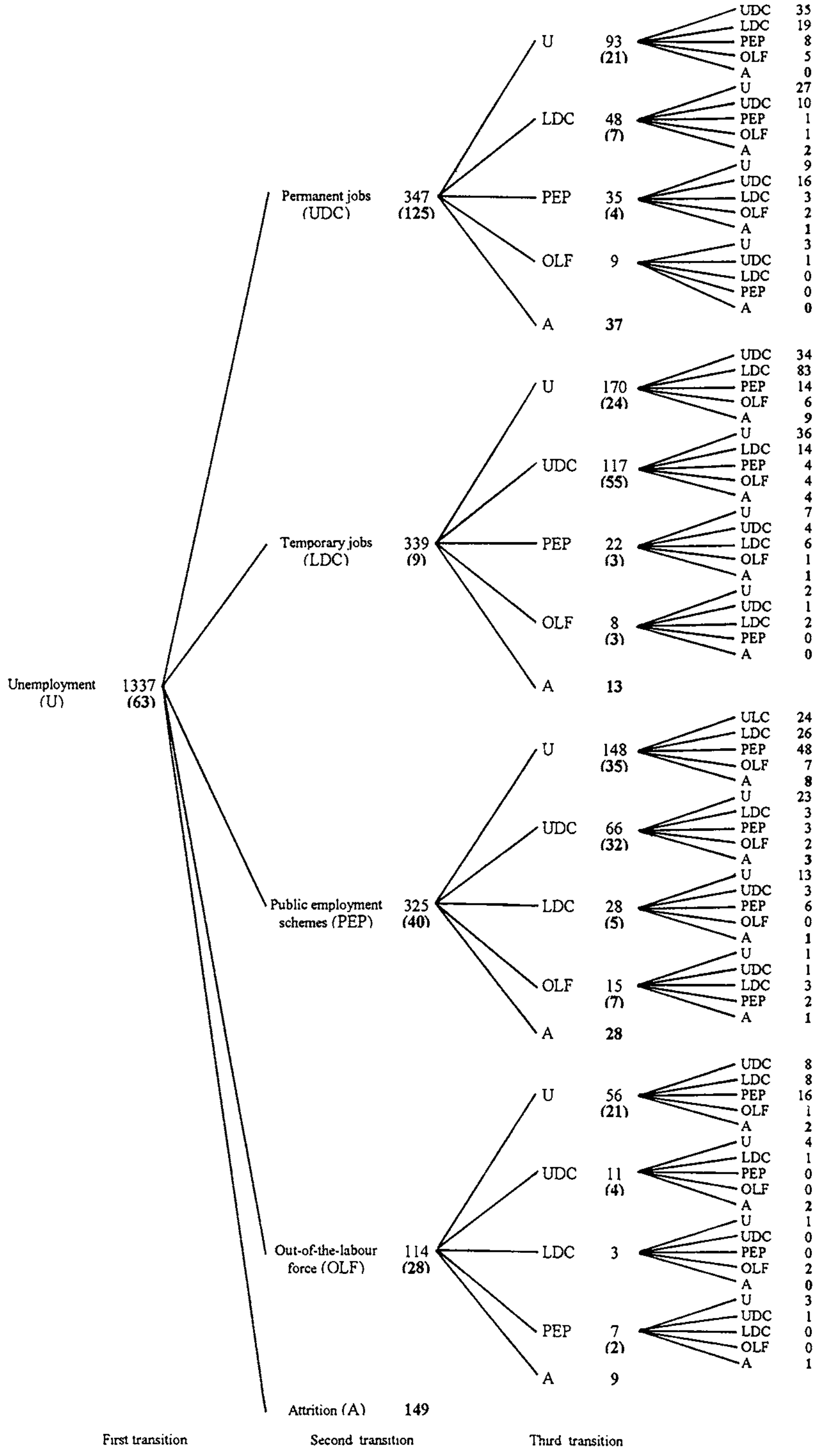
Because public employment policies are mainly oriented towards low-educated or low-experienced young people, we have stratified the young male subsample according to the educational level. Four groups may be distinguished (see Table 2.1):

- the first one has no diploma (less than 9 years of schooling): it represents 50·33% of the sample,
- the second one gets a technical school certificate (called a C.A.P. or a B.E.P. in France, and obtained after 11 years of schooling): 30·3% of the sample get such a diploma,
- the third group corresponds to young men holding at least a high-school diploma (more than 12 years of schooling): it represents 9·2% of the subsample,
- finally, 136 individuals (10·17%) gave no information on their education level.

Figure 2.4 shows the proportions of these four subgroups who were unemployed, employed either in a permanent job, a temporary job or a public employment programme each month from August 1986 to May 1988 (these proportions are calculated without incorporating the individuals having moved to attrition). It is obvious that, for the highly educated people, the unemployment rate is lower at the end of this period, while their rate of employment in permanent jobs is higher (65% vs. 30% for the young men with no diploma). Now let us consider the proportions in jobs resulting from public employment policies: they are higher for young men without a diploma or non-respondents. For young men with at least a high-school diploma, the proportion in PEP jobs is around 10% at the end of the observation period.

One objective of our study is to compare programme effects for different educational levels. Consequently, we concentrate the statistical analysis on the most represented strata: males without a diploma and males with a technical school certificate satisfying the age condition for programme participation.[3] Descriptive statistics giving numbers of individual transitions over the observation period show that these two groups move more intensively between labour force states than the highly educated people. For instance, the maximum number of transitions recorded over this period is equal to 11, indicating that young males with a low educational level are highly mobile.

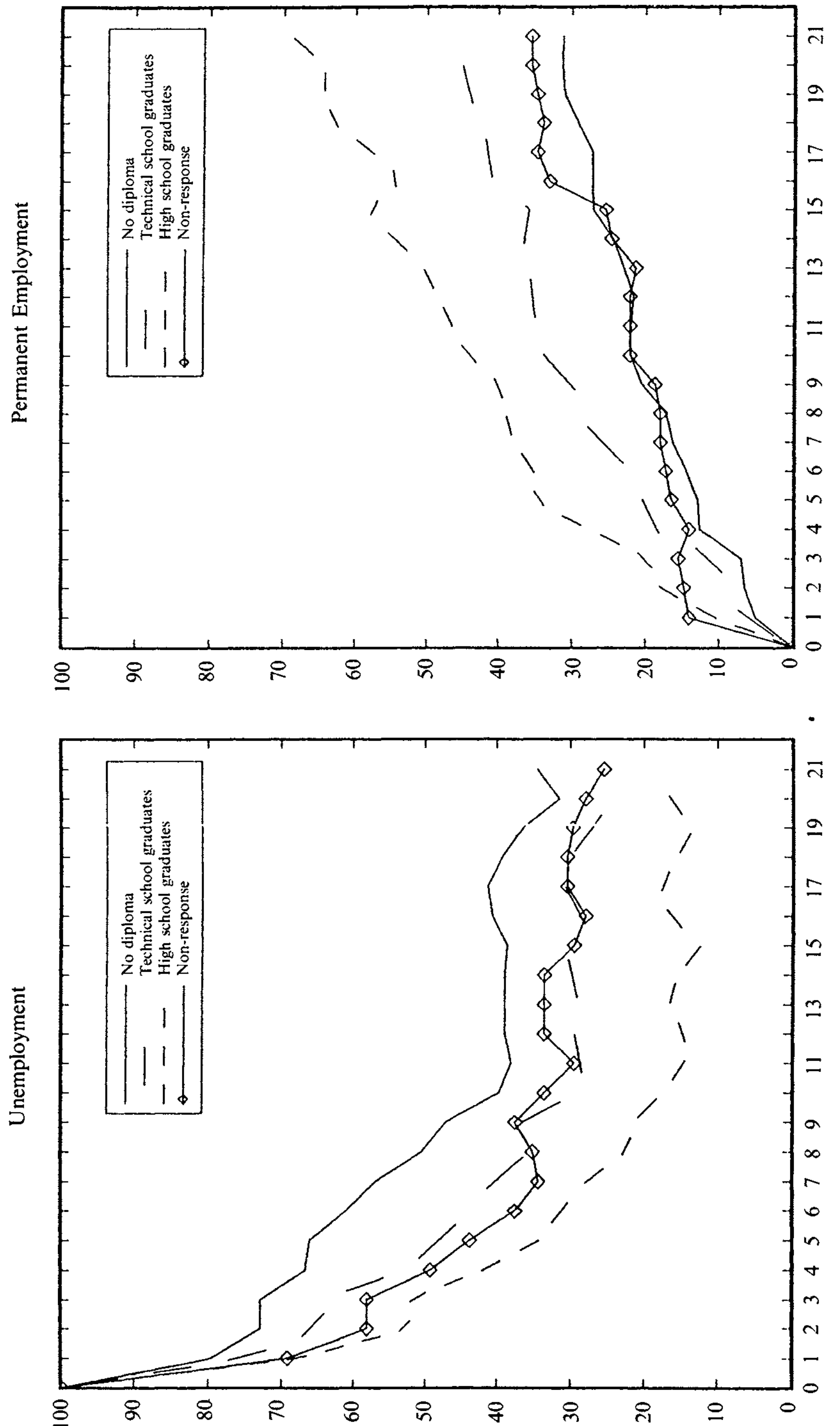
3. To simplify, we keep males who are more than 16 years old in August 1986 and less than 26 in May 1988.



Remark : Between brackets are the numbers of right-censored spells.

FIGURE 2.3

Frequencies of the first three transitions


Permanent Employment
No diploma
Technical school graduates
High school graduates
Non-response
Unemployment
No diploma
Technical school graduates
High school graduates
Non-response

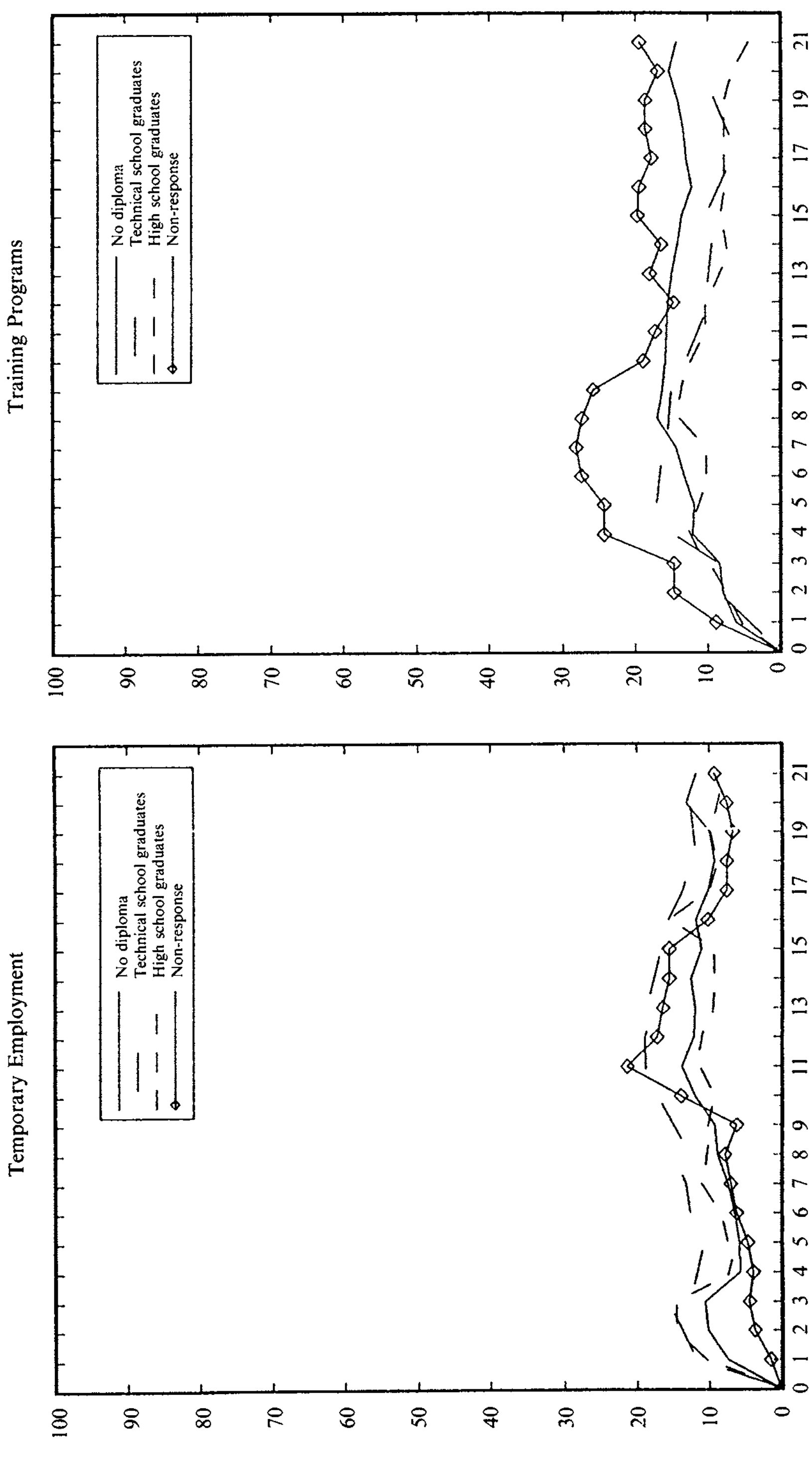


FIGURE 2.4
Monthly proportions in four labour force states

III. MODELLING INDIVIDUAL LABOUR MARKET TRANSITIONS

III.1. *General framework and notations*

We suppose that each worker in the population is subject to a participation process[4] Y_t describing his current state in the labour market at time t ($t \geqq 0$). Considering the problem to be analysed and the specificities of our data set, we assume that the process Y_t takes its values at any instant t in the discrete state space $E = \{j \in \mathbb{N},\ 1 \leqq j \leqq 6\}$, where the index j labels the following states:

1. unemployment,
2. employment in a job with an unlimited duration contract (permanent employment),
3. employment in a job with a limited duration contract (temporary employment),
4. employment in a job resulting from a public employment policy (PEP job),
5. out-of-labour force state,
6. attrition state.

In fact, the survey permits us to distinguish between five kinds of PEP jobs: apprenticeship contracts, adaptation and qualification contracts, community jobs (T.U.C.), initiation courses (S.I.V.P.), and courses for 16-to-25 year-olds. But considering the small numbers of observed transitions, we aggregate the different kinds of PEP jobs into one state. The attrition state is an absorbing state which can be reached only after the sampling date T_0 (August 1986). The index l is used for indicating the rank order of a spell in any individual event history. This index can take a positive or negative integer value: $l=0$ refers necessarily to the unemployment spell sampled at T_0, $l=1$ corresponds to the first spell (if any) observed after this sampled unemployment spell, $l=-1$ corresponds to the spell just preceding this unemployment spell, and so on. Consequently, the maximal value taken by l for an individual observation indicates the number of transitions experienced by the worker after the sampling date T_0. Individual participation histories are retrospectively observed at times T_1 (November 1986), T_2 (May 1987), T_3 (November 1987) and T_4 (May 1988). Any "complete" (without attrition) history is right-censored at T_4. A transition to attrition may occur at any time between T_{m-1} and T_m ($m=1, \ldots, 4$), and not at times $T_0, \ldots, T_4$ exactly. For a worker,[5] τ_l denotes the random date of entrance into the lth spell of his observed participation history: consequently, Y_{τ_l} is the state occupied by an individual during the lth spell of his history, and $U_l = \tau_{l+1} - \tau_l$ is a (positive) random variable representing the time spent by the worker in this lth spell.

In our data set, individuals are sampled in the unemployed population at date T_0 (August 1986): consequently, the worker has already spent a time $\bar{U}_0 = T_0 - \tau_0$ in unemployment at this date. This sojourn time $\bar{U}_0$ is obviously an incomplete (right-censored) duration: then $R_0 = U_0 - \bar{U}_0 = \tau_1 - T_0$ denotes the residual duration of the sampled unemployment spell ending with a transition to state Y_{τ_1} at time τ_1.

For simplifying the model, we assume that individual transitions in the labour market do not directly depend on calendar time through seasonal or business cycle effects.[6] Moreover they are supposed to be independent of the worker's age. This is mainly for practical

4. For a general presentation of the econometric treatment of transition data, see for example the textbook by Lancaster (1990) or surveys by Florens and Fougère (1992) or Fougère and Kamionka (1992*b*).

5. We delete the person-specific index to simplify formulas.

6. Obviously, this is a strong (and probably unrealistic) assumption: however, Fougère and Kamionka (1992*a*) found empirical evidence of the relative time-homogeneity of individual transition intensities over the period 1986–1988 in France. For the incorporation of seasonal and business-cycle effects in duration or transition models, see De Toldi, Gouriéroux and Monfort (1995) or Imbens and Lynch (1992).

reasons: including age as a covariate in the twenty-five possible transitions would unreasonably expand the already long list of coefficients to be estimated. To some extent, the effects of age at entry into the sample will be captured by the unobserved heterogeneity term; however, we must recognize that a random term is an imperfect substitute to age.[7]

Consequently, the individual time axis may be scaled so that its origin ($t=0$) is set equal to the date at which a worker enters the labour market for the first time: then τ_l measures the time difference between this entry date (which is observed in the data set) and the date at which the individual experiences his lth transition in the labour market. As an illustration of the sampling scheme, Figure 3.1 represents a realization of the labour market transition process described above. This figure shows that the worker is firstly unemployed for a duration $U_{-2}=\tau_{-1}$, then is employed in a temporary job with a duration equal to $U_{-1}=\tau_0-\tau_{-1}$, then enters once again unemployment (where he is sampled at date T_0 and surveyed at date T_1) for a duration equal to $U_0=\tau_1-\tau_0$, then finds a job under an "adaptation-type" contract whose duration is $U_1=\tau_2-\tau_1$, and then moves to a permanent job in which he stays for a duration greater than $\bar{U}_2$: this last duration is right-censored at date T_4 by the end of the observation schedule.

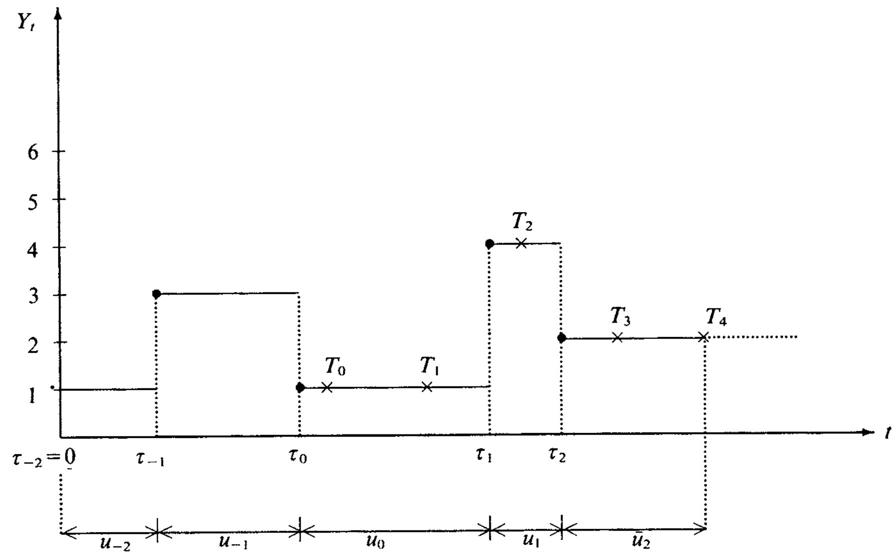


FIGURE 3.1
A realization of the labour market transition process Y_t

III.2. *Distribution of the individual transition processes*

Now we assume that individual labour market transitions are governed by intensity functions of the mixed proportional hazard (MPH) type (see Elbers and Ridder (1982) and Ridder (1990) for the presentation and the identifiability of MPH models applied to single-spell duration data, and Flinn and Heckman (1982, 1983), Aalen (1987) and Honoré

7. In less-parameterized versions of the econometric model, we introduced among covariates affecting rates of exit from unemployment a dummy variable indicating if the worker's age was greater than 21 years old at the beginning of the unemployment spell. Generally, this variable was found to have no statistically significant effect.

(1993) for extensions of such models to multi-state multi-spell duration data). More specifically, we assume that the intensity of transition to state k after a sojourn duration equal to u_l in state j ($j \neq k$), during the lth spell of his labour market transition process, is defined by

$$h_{jk}(u_l \mid \beta_{jk}, X_{jk}(\tau_l+u_l), v_{jk}) = h_{jk}^{(0)}(u_l) \exp[\beta'_{jk} X_{jk}(\tau_l+u_l)] v_{jk} \quad \text{for } k \neq j, \tag{1}$$

where:

- $h_{jk}^{(0)}(\cdot)$ is a positive baseline intensity function, whose form may depend on the origin (j) and destination (k) states, but not on the rank order (l) of the current spell in the transition history,
- $X_{jk}(\cdot)$ is a vector of time-varying individual covariates whose value at the transition time (τ_l+u_l) is supposed to affect a move from state j to state k ($k \neq j$) through a vector of unknown parameters β_{jk} (to be estimated),
- and v_{jk} is a positive random variate with c.d.f. F_{jk}, whose specification may depend on states j and k but not on the rank order of the spell, and which is intended to capture the effect of individual unobserved heterogeneity on transition from state j to state k.

Given the number of possible transitions, we restrict the size of the multivariate random vector (v_{jk}) by assuming that $v_{jk} = v_k$, for any $j \in E$, which means that the heterogeneity term affecting the intensity of transition from state j to state k ($k \neq j$) is specific to the destination state k. This last assumption implies, for example, that an individual with a relatively high value for the unobserved component v_5 has a loose attachment to the labour market and is more likely to move to the non-participation state, whatever the state (employment or unemployment) he currently occupies. Alternatively, an unskilled or disadvantaged worker should have much more willingness to accept subsidized course-type jobs or training programmes and so have a higher value for the unobserved component v_4.

The vector of time-varying covariates $X_{jk}(\cdot)$ can be decomposed into two sub-vectors $X_{jk}^0(\tau_l)$ and $X_{jk}^1(\tau_l+u_l)$:

- the value of the first one $X_{jk}^0(\tau_l)$ is fixed at the date of entrance into the lth spell and then remains constant through the spell: typically, this vector includes time-independent covariates and also covariates describing the past individual history in the labour market (number of previous spells of unemployment, total sojourn duration in these spells, last state occupied, ...);
- the second sub-vector of covariates $X_{jk}^1(\tau_l+u_l)$ incorporates covariates varying through the lth spell; in our application, we consider exclusively one such covariate: an indicator process $Z(\tau_l+u_l)$ taking the value one if the state occupied by the individual during the lth spell of his transition process is unemployment and if he is still receiving unemployment insurance benefits after a time u_l spent in this spell, the value zero otherwise. However, the survey does not give any information on the amount of these benefits and on the duration of the period of qualification to receive unemployment insurance.

Using assumptions made on X_{jk}, the transition intensity (1) may be written

$$h_{jk}(u_l \mid \beta_{jk}, X_{jk}(\tau_l+u_l), v_k) = h_{jk}^{(0)}(u_l) \exp[\beta_{jk}^{0\prime} X_{jk}^0(\tau_l) + \gamma_{jk} Z(\tau_l+u_l)]\, v_k, \tag{2}$$

where

$$\beta_{jk} = (\beta_{jk}^{0\prime}, \gamma_{jk})', \; X_{jk}(\tau_l+u_l) = [X_{jk}^0(\tau_l), Z(\tau_l+u_l)]',$$

and

$$Z(\tau_l+u_l)=\begin{cases}1 & \text{if } u_l\leqq D_l,\\ 0 & \text{elsewhere.}\end{cases}$$

D_l is the potential duration of qualification for unemployment insurance benefits during the lth spell if this spell is an unemployment spell, i.e. $j=1$ (if $j\neq 1$, D_l is necessarily equal to zero and $Z(\tau_l+u_l)$ is constantly zero through the lth spell). Consequently, the conditional density function (3) of the duration in state j during the lth spell, given that this spell starts at time τ_l and ends at time τ_l+u_l with a transition to state k, is (see Fougère and Kamionka (1992*b*, pp. 474–475) for a proof)

$$\begin{aligned} g_{jk}(u_l|\beta_j, X_j(\tau_l+u_l), v) &= h_{jk}(u_l|\beta_{jk}, X_{jk}(\tau_l+u_l), v_k)\\ &\quad\times\exp\left(-\int_0^{u_l}\textstyle\sum_{k'=1,\,k'\neq j}^{K} h_{jk'}(t|\beta_{jk'}, X_{jk'}(\tau_l+t), v_{k'})dt\right)\\ &= h_{jk}^{(0)}(u_l)\exp\left[\gamma_{jk}Z(\tau_l+u_l)+\beta_{jk}^{0\prime}X_{jk}^{0}(\tau_l)\right]v_k\\ &\quad\times\exp\left(-\textstyle\sum_{k'=1,\,k'\neq j}^{K}\exp\left[\beta_{jk}^{0\prime}X_{jk}^{0}(\tau_l)\right]v_k\right.\\ &\quad\times\left\{Z(\tau_l+u_l)\exp(\gamma_{jk'})\int_0^{u_l}h_{jk'}^{(0)}(t)dt+(1-Z(\tau_l+u_l))\right.\\ &\quad\left.\left.\times\left(\exp(\gamma_{jk'})\int_0^{D_l}h_{jk'}^{(0)}(t)dt+\int_{D_l}^{u_l}h_{jk'}^{(0)}(t)dt\right)\right\}\right), \end{aligned}\tag{3}$$

where the vectors β_j, $X_j(\cdot)$ and v are defined by $\beta=[\beta_{jk}]_{k\neq j}$, $X_j(\cdot)=[X_{jk}(\cdot)]_{k\neq j}$, $v=[v_k]_{k\in E}$, and where $K=6$ if transitions to attrition state are allowed, $K=5$ otherwise. The conditional density function defined in (3) is the likelihood contribution of the lth spell when it is not right-censored (i.e. when $\tau_{l+1}=\tau_l+u_l\leqq T_4$). When the lth spell ends after T_4, the contribution of this right-censored spell to the likelihood function is

$$\begin{aligned} &S_j(T_4-\tau_l|\tau_l, \beta_j, X_j(T_4), v)\\ &\quad=\text{prob}\,(u_l>T_4-\tau_l|\tau_l, \beta_j, X_j(T_4), v)\\ &\quad=\exp\left(-\int_0^{T_4-\tau_l}\textstyle\sum_{k'=1,\,k'\neq j}^{K} h_{jk'}(t|\tau_l, \beta_{jk'}, X_{jk'}(\tau_l+t), v_{k'})dt\right), \end{aligned}\tag{4}$$

where $S_j(\cdot\,|\,\cdot)$ is the conditional survival function of the duration in state j. If an individual moves to the attrition state during the lth spell between two successive interview dates T_{m-1} and T_m ($m=1,\ldots,4$), then the contribution of this spell to the likelihood function is

$$\begin{aligned} &\text{prob}\,(u_l\in\,]T_{m-1}-\tau_l, T_m-\tau_l[\,|\tau_l, Y_{\tau_l}=j, \beta_j, X_j(T_{m-1}), v)\\ &\quad=S_j(T_m-\tau_l|\tau_l, \beta_j, X_j(T_{m-1}), v)-S_j(T_{m-1}-\tau_l|\tau_l, \beta_j, X_j(T_{m-1}), v). \end{aligned}\tag{5}$$

However some difficulty may appear in the treatment of transitions towards the attrition state. In fact, suppose an individual is observed to leave the panel between two consecutive interviews. The model states that there is a positive probability that the individual makes one or more labour market transitions between the last interview at which he participated and the moment at which the duration of panel survey participation is completed. Past states should affect the exit rate out of the panel, so every time a transition is made, the exit rate out of the panel should change. The easiest way to avoid this difficulty is to make the exit rates out of the panel independent of past labour market states.[8]

III.3. *Correction of the stock sampling bias*

It is well known that sampling from the stock of unemployed people at a given date T_0 may induce biased estimates for parameters of the distribution of durations in that state or in subsequent states (employment, out-of-labour force, etc.). The bias has two components: firstly, a length-bias due to the fact that the sampling probability of a given spell is generally proportional to its elapsed duration (or length), and secondly, an inflow-rate bias, resulting from the dependence of this probability on the rate of transition into unemployment at the starting date τ_0 of that spell.[9]

Like other data sets used in similar studies (see, for example, Ridder (1986), Van den Berg, Lindeboom and Ridder (1994)), the INSEE survey does not register the individual transition history $\Omega(\tau_0)$ preceding the entry into the unemployment spell sampled at T_0, with the exception of the information on the state occupied just before entering this unemployment spell. For circumventing this problem, one way is to assume that the entry rate into unemployment does not depend directly on the calendar time, but factorizes in terms of v_1 (the unobserved heterogeneity term affecting the intensities of transition towards unemployment) and $X(\tau_0)$, which denotes the vector of individual covariates at the time of entry into unemployment (see Van den Berg, Lindeboom and Ridder (1994, p. 424)). In other terms, if $q(\cdot\,|\,\cdot)$ denotes the inflow rate, then we assume that

$$q(\tau_0\,|\,v_1, X(\tau_0)) = q_1(v_1) \times q_2(X(\tau_0)) \propto v_1 \times q_2(X(\tau_0)), \tag{6}$$

with $q_1(\cdot) > 0$ and $q_2(\cdot) > 0$. Recalling that $\bar{U}_0 = T_0 - \tau_0$ denotes the time already spent in unemployment by an individual at the sampling date, then the probability that an individual with a given unobserved heterogeneity term v and a given covariate vector $X(\tau_0)$ is in the stock of unemployed people at T_0 equals

$$\begin{aligned} P_s(v, X(\tau_0)) &= \int_0^\infty q(\tau_0\,|\,v, X(\tau_0)) \operatorname{prob}(U_0 > \bar{U}_0\,|\,v, X(\tau_0)) d\bar{U}_0 \\ &\propto v_1 \times q_2(X(\tau_0)) \times \int_0^\infty \exp\left\{-\textstyle\sum_{k=2}^5 \displaystyle\int_0^{\bar{U}_0} h_{1k}(t\,|\,\beta_{1k}, X_{1k}(\tau_0), v_k) dt\right\} d\bar{U}_0. \end{aligned}$$

Consequently, the probability to be sampled in the stock given the observable heterogeneity only is

$$P_s(X(\tau_0)) = \int_{v \in \Lambda} P_s(v, X(\tau_0)) f(v\,|\,\alpha) dv, \tag{8}$$

8. We thank a referee for this suggestion.

9. Papers by Ridder (1984), Van den Berg, Lindeboom and Ridder (1994) and Gouriéroux and Monfort (1992) develop statistical analysis of such biases in the context of unemployment duration models.

where $f(\cdot|\alpha)$ is the joint density function of the vector v and Λ is the support of the distribution of v. Finally, the likelihood contribution of an individual with covariates $X(\tau_0)$ at entry and with observed transition history $(\tau_l, Y_{\tau_l})_{l=0,1,\ldots,\bar{L}}$ is the conditional density of this sequence given that the individual was in the unemployment stock at date T_0, $\bar{L}=0, 1, 2, \ldots$ being the number of transitions observed for this individual before T_4. So this likelihood function has the general form

$$\begin{aligned}
&\mathscr{L}((\tau_l, Y_{\tau_l})_{l=0,1,\ldots,\bar{L}}|X(\tau_0), \beta, \alpha)\\
&= \Bigg[\int_{v\in\Lambda} q(\tau_0|v_1, X(\tau_0))S_{Y_{\bar{L}}}(T_4-\tau_{\bar{L}}|\beta_{Y_{\bar{L}}}, X_j(T_4), v)\\
&\quad\times\left\{\prod_{l=0}^{\bar{L}} g_{Y_{l-1},Y_l}(u_{l-1}|\beta_{Y_{l-1}}, X_{Y_{l-1}}(\tau_{l-1}+u_{l-1}), v)\right\}f(v|\alpha)dv\Bigg]\times[P_s(X(\tau_0))]^{-1}\\
&\propto \Bigg[\int_{v\in\Lambda} v_1\times S_{Y_{\bar{L}}}(T_4-\tau_{\bar{L}}|\beta_{Y_{\bar{L}}}, X_j(T_4), v)\\
&\quad\times\left\{\prod_{l=0}^{\bar{L}} g_{Y_{l-1},Y_l}(u_{l-1}|\beta_{Y_{l-1}}, X_{Y_{l-1}}(\tau_{l-1}+u_{l-1}), v)\right\}f(v|\alpha)dv\Bigg]\\
&\quad\times\left[\int_{v\in\Lambda} v_1\left(\int_0^{\infty}\exp\left\{-\sum_{k=2}^{5}\int_0^{\bar{U}_0} h_{1k}(t|\beta_{1k}, X_{1k}(\tau_0), v_k)dt\right\}d\bar{U}_0\right)f(v|\alpha)dv\right]^{-1}, \qquad (9)
\end{aligned}$$

where Y_l is the state occupied during the lth spell of the observed transition history. Given formulas (2), (3) and (4), a standard maximum likelihood procedure allows to obtain consistent estimates of $\beta=(\beta_{jk})_{k\neq j}$, of parameters of baseline hazard functions $h_{jk}^{(0)}$ and of parameters α of the joint density $f(\cdot)$ of the vector v.

III.4. *Specification issues*

Besides the introduction of a time-varying unemployment benefits entitlement variable, we allow the baseline rates of transition from unemployment to permanent or temporary employment and to PEP jobs to be piecewise constant. More precisely, we assume that

$$\begin{aligned}
h_{1k}^{(0)}(u) &= \exp(\delta_{0k}) && \text{if } u\leqq 6 \text{ months},\\
&= \exp(\delta_{0k}+\delta_{2k}) && \text{if } 6<u\leqq 12 \text{ months}, \qquad \text{for } k=2, 3, 4. \qquad (10)\\
&= \exp(\delta_{0k}+\delta_{3k}) && \text{if } u>12 \text{ months},
\end{aligned}$$

This specification allows for possible non-monotone evolutions of the exit rates from unemployment, without increasing dramatically the number of parameters. All other transition intensities are supposed to be constant through time. For the distribution of the unobserved heterogeneity vector $v=(v_k)_{k=1,\ldots,K}$, we consider two alternative assumptions. Firstly, following Flinn and Heckman (1982), we assume that components $(v_k)_{k=1,\ldots,K}$ are generated by a common normally distributed random variate w such as

$$v_k=\exp(\alpha_k w), \qquad (11)$$

where $w\sim I\mathscr{N}(0, 1)$.

Obviously, this specification allows unobserved explanatory variables v_k to be mutually dependent. However, this dependence is too restrictive, because correlation between log v_k and log $v_{k'}$ $(k' \neq k)$ can only equal 0, 1 or -1, according to the fact that $\alpha_k \alpha_{k'} = 0$, $\alpha_k \alpha_{k'} > 0$ or $\alpha_k \alpha_{k'} < 0$. A way of producing more flexible dependence is to assume that components v_k have discrete multivariate distributions with a finite number of points of support. For instance, Van den Berg (1995) examines the range of values that correlation of the duration variables can attain in bivariate mixed proportional hazard models. It turns out that when the bivariate vector of unobserved heterogeneity terms has a bivariate discrete distribution with two or more points of support for each component, and the locations of these points are not fixed in advance, then all possible values can be reached. On the other hand, when this vector has a log-normal distribution, then the range of values that can be attained is smaller.

In our model, a six-dimensional discrete distribution would be burdensome, but it is still possible to estimate without too much computational difficulty a two-factor loading model in which

$$v_k = \exp\,(\alpha_{k1} w_1 + \alpha_{k2} w_2), \tag{12}$$

and

$$\begin{aligned} \text{prob}\,\{(w_1, w_2) = (w_{11}, w_{21})\} &= p_1, \\ = (w_{12}, w_{21})\} &= p_2, \\ = (w_{11}, w_{22})\} &= p_3, \\ = (w_{12}, w_{22})\} &= 1 - p_1 - p_2 - p_3, \\ w_{ij} \in \mathbb{R}, \qquad i, j &= 1, 2. \end{aligned}$$

For this second model, we have to estimate K couples $(\alpha_{k1}, \alpha_{k2})$ of parameters, four points of support w_{ij} and three probabilities of the form

$$p_i = \frac{\exp\,(\mu_i)}{1 + \sum_{j=1}^{3} \exp\,(\mu_j)}, \qquad i = 1, 2, 3. \tag{13}$$

The test for model selection developed by Vuong (1989) may be used here as a criterion of choice between the two alternative models (11) and (12). These two models are overlapping and their intersection is the model without unobserved heterogeneity. Consequently, the selection test is the two stage sequential test proposed by Vuong (1989, p. 321).

IV. RESULTS

As explained in Section III, the different public measures are aggregated into one state, called "public employment programmes" (PEP). So the statistical model allows for transitions among six states, which are unemployment (U), regular employment with an unlimited duration labour contract (UDC), temporary employment with a limited duration labour contract (LDC), employment in a public employment programme (PEP), out-of-labour force (OLF), and attrition (A).[10] Here we consider strata composed of men who were less than 26 years old in November 1986 and who get either a technical school certificate or no diploma at all. Table 4.1 contains parameters estimates of models (11)

10. In the subsample of young men holding a technical school certificate, attrition state is omitted because of the small number of concerned transitions; transitions towards the attrition state are treated as right-censored spells.

and (12) (denoted models A and B, respectively) with individual heterogeneity and correction of the stock sampling bias. Covariate vectors include a time-varying variable indicating if the individual is qualified for the unemployment insurance (UI) system during each month of the unemployment spell, and also dichotomous variables indicating the state occupied just before entering the current state. Among previous states, we make the distinction between four types of employment programmes:

- qualification, adaptation or apprenticeship contracts,
- public interest jobs (TUC).
- courses for preparation to the working life,
- other courses.

IV.1. *Transition intensities*

The results show that the previous occurrence of a public employment programme affects only some transition intensities. The sign and the magnitude of the statistically significant effects depend on the type of programme which has been previously followed. Introducing unobserved heterogeneity terms improves the adequacy of the models.[11] The result of the Vuong test for model selection is inconclusive: models (11) and (12) cannot be discriminated given the data. Generally, parameter estimates do not vary much from one model to the other. However, they differ significantly for some variables of interest.[12] Let us first comment upon the results which are stable. The impact of programmes on subsequent unemployment durations depends crucially on the educational level. For young men without a diploma (the least educated group), the previous occurrence of an apprenticeship, qualification or adaptation contract induces a higher intensity of transition from unemployment to regular (UDC) jobs, while it has no effect on the same transition for young men with a professional education level. At the same time, the experience of a community job in the public sector (TUC) has no effect on the intensity of transition from unemployment to regular or temporary employment for the sample without a diploma, while it decreases significantly this transition intensity for young men with a professional or technical diploma. In a sense, these results provide a first criterion for ranking different public employment programmes. Obviously, whatever the educational level is, training programmes in the private sector (respectively, in the public sector) have the most favourable (respectively, the poorest) impact on unemployment outcomes. Programmes involving a higher level of on-the-job training, such as apprenticeship or qualification contracts, are essentially beneficial to the less educated young people, who may increase their human capital and work experience through these programmes. In contrast, for more educated young men, programmes in the public sector (TUC jobs) decrease the intensity of transition from the subsequent unemployment spell to regular employment: one possible explanation of this result is that participation in such programmes may act as a signal of low employment performance, especially for young people who have initially received some professional education.[13] Another noticeable result is the high degree of state recurrence, in spite

11. Parameter estimates for the model without unobserved heterogeneity are not presented here. For each model with unobserved heterogeneity, a likelihood ratio test leads to the strong rejection of the nested model without unobserved heterogeneity.

12. This fact confirms the results of Heckman and Singer (1984) who gave evidence on the sensitivity of parameter estimates obtained from econometric models for single duration data to assumed functional forms for the distribution of unobserved variables.

13. This result was also found by Gritz (1993), but with a relatively small number of government trainees and without distinguishing between different levels of education.

TABLE 4.1 (beginning)

Transition intensities from unemployment

Variables	Young men without any diploma ($N=672$) Model A	Model B	Young men with a technical school certificate ($N=405$) Model A	Model B
U→UDC				
Intercept	**−4·269 (0·489)**	**−4·299 (0·098)**	**−4·115 (0·674)**	**−3·888 (0·124)**
Intercept 6–12 months	**−0·506 (0·140)**	**−0·490 (0·100)**	−0·126 (0·120)	−0·080 (0·120)
Intercept >12 months	**−0·363 (0·171)**	**−0·319 (0·093)**	−0·044 (0·067)	**0·250 (0·119)**
Qualification for UI	0·047 (0·438)	**−0·255 (0·098)**	0·300 (0·754)	0·138 (0·124)
Previous occurrence of:				
QC, AC, App	*0·979 (0·606)*	**1·606 (0·120)**	−0·264 (1·221)	−0·059 (0·156)
TUC	−0·120 (0·390)	0·000 (0·116)	**−0·753 (0·360)**	**−0·746 (0·152)**
SIVP	**0·485 (0·239)**	**0·840 (0·117)**	0·493 (0·343)	**0·416 (0·147)**
Other courses	0·300 (0·339)	**0·538 (0·113)**	0·045 (0·494)	−0·190 (0·150)
UDC	**0·902 (0·151)**	**0·922 (0·093)**	**0·386 (0·201)**	**0·389 (0·118)**
LDC	**0·403 (0·186)**	**0·405 (0·094)**	*0·334 (0·200)*	**0·341 (0·114)**
U→LDC				
Intercept	**−3·343 (0·813)**	**−3·107 (0·101)**	**−3·445 (0·333)**	**−3·658 (0·131)**
Intercept 6–12 months	−0·151 (0·209)	**−0·197 (0·094)**	−0·011 (0·203)	−0·113 (0·113)
Intercept >12 months	**−0·411 (0·178)**	**−0·446 (0·095)**	0·069 (0·175)	−0·077 (0·125)
Qualification for UI	**−0·912 (0·461)**	**−1·275 (0·101)**	−0·134 (0·276)	−0·178 (0·127)
Previous occurrence of:				
QC, AC, App	0·167 (1·065)	**0·383 (0·121)**	−0·752 (0·914)	0·032 (0·157)
TUC	0·131 (0·219)	0·086 (0·114)	**−0·772 (0·343)**	**−0·828 (0·152)**
SIVP	**1·010 (0·315)**	**0·718 (0·116)**	0·227 (0·559)	**0·371 (0·148)**
Other courses	−0·255 (0·397)	−0·186 (0·116)	0·855 (0·587)	**1·360 (0·149)**
UDC	**−0·363 (0·131)**	**−0·386 (0·101)**	0·165 (0·148)	0·152 (0·124)
LDC	**0·537 (0·160)**	**0·523 (0·089)**	**0·660 (0·156)**	**0·750 (0·108)**
U→PEP				
Intercept	**−4·619 (0·792)**	**−4·844 (0·100)**	**−3·257 (0·727)**	**−3·074 (0·123)**
Intercept 6–12 months	−0·006 (0·161)	0·066 (0·096)	−0·303 (0·230)	**−0·328 (0·132)**
Intercept >12 months	0·088 (0·191)	**0·223 (0·092)**	0·153 (0·145)	*0·221 (0·126)*
Qualification for UI	0·688 (0·704)	**0·766 (0·099)**	−0·521 (0·696)	**−0·664 (0·123)**
Previous occurrence of:				
QC, AC, App	**1·229 (0·362)**	**0·795 (0·118)**	0·359 (0·749)	**0·663 (0·155)**
TUC	**0·912 (0·078)**	**0·877 (0·108)**	**1·334 (0·380)**	**1·280 (0·139)**
SIVP	**0·805 (0·330)**	**0·610 (0·115)**	**1·123 (0·181)**	**1·130 (0·144)**
Other courses	0·294 (0·317)	0·160 (0·111)	**0·853 (0·229)**	**0·633 (0·148)**
UDC	**−0·420 (0·134)**	**−0·458 (0·101)**	−0·417 (0·344)	**−0·440 (0·133)**
LDC	*−0·205 (0·126)*	**−0·186 (0·094)**	**−0·528 (0·234)**	**−0·489 (0·126)**
U→OLF				
Intercept			**−4·003 (0·888)**	**−3·777 (0·117)**
Qualification for UI			1·477 (1·001)	1·369 (0·117)
U→A				
Intercept	**−4·421 (1·182)**	**−4·921 (0·104)**		
Qualification for UI	−0·544 (1·210)	**−0·403 (0·104)**		

of the introduction of time-constant unobserved heterogeneity into the model. For example, the previous experience of a regular job just before the entry into the current unemployment spell increases the probability of transition to another regular job at the end of the current unemployment spell. The same recurrence effects appear for temporary jobs and youth employment programmes. With these data and with this reduced-form model, it is difficult to know if these recurrence effects are mainly due to workers' preferences or to the selection carried out by employers during the hiring process: nevertheless, they could be compatible with a segmented labour market in which past employment histories provide information on applicants to future employers, and which may result,

TABLE 4.1 (intermediate)

Transition intensities from regular and temporary jobs

Variables	Young men without any diploma ($N=672$)		Young men with a technical school certificate ($N=405$)	
	Model A	Model B	Model A	Model B
UDC→U				
Intercept	**−3·003 (0·117)**	**−2·227 (0·086)**	**−3·266 (0·061)**	**−3·259 (0·105)**
Previous occurrence of:				
SIVP	−0·363 (0·591)	**−0·777 (0·119)**	−0·836 (1·079)	−0·672 (0·155)
Other PEP jobs	0·320 (0·317)	−0·050 (0·114)	**0·828 (0·210)**	**0·877 (0·142)**
LDC	0·119 (0·446)	*0·176 (0·108)*	−0·437 (0·355)	**−0·588 (0·140)**
UDC→LDC				
Intercept	**−3·966 (0·117)**	**−4·277 (0·103)**	**−4·078 (0·138)**	**−4·057 (0·135)**
Previous occurrence of:				
PEP jobs	*−1·240 (0·653)*	**−1·513 (0·120)**		
LDC	**−2·210 (0·365)**	**−1·738 (0·119)**	**−0·438 (0·136)**	**−1·041 (0·145)**
UDC→PEP				
Intercept	**−4·556 (0·162)**	**−4·179 (0·108)**	**−4·510 (0·363)**	**−4·750 (0·136)**
Previous occurrence of:				
PEP jobs	0·583 (0·671)	0·097 (0·118)		
LDC			−1·131 (1·087)	−0·894 (0·154)
UDC→OLF: Intercept	**−5·992 (0·482)**	**−6·280 (0·118)**	**−5·321 (0·249)**	**−5·422 (0·143)**
UDC→A: Intercept	**−4·406 (0·219)**	**−4·500 (0·109)**		
LDC→U				
Intercept	**−1·625 (0·265)**	**−1·636 (0·080)**	**−1·891 (0·120)**	**−2·146 (0·095)**
Previous occurrence of:				
PEP	**−0·936 (0·485)**	**−1·084 (0·117)**	**−1·462 (0·278)**	**−1·319 (0·153)**
UDC	**−0·663 (0·211)**	**−0·430 (0·110)**	*−0·363 (0·219)*	−0·226 (0·141)
LDC→UDC				
Intercept	**−2·625 (0·288)**	**−3·017 (0·093)**	**−2·447 (0·155)**	**−2·288 (0·106)**
Previous occurrence of:				
PEP	−1·115 (0·703)	**−1·056 (0·120)**	0·038 (0·391)	**−0·367 (0·151)**
UDC	**−0·643 (0·329)**	**−0·810 (0·115)**	0·169 (0·358)	−0·087 (0·143)
LDC→PEP				
Intercept	**−4·663 (0·367)**	**−4·753 (0·114)**	**−4·213 (0·300)**	**−3·962 (0·133)**
Previous occurrence of:				
PEP	**1·854 (0·497)**	**1·702 (0·119)**	**0·995 (0·515)**	**0·881 (0·152)**
LDC→OLF: Intercept	**−4·813 (0·579)**	**−4·614 (0·117)**	**−4·789 (0·263)**	**−4·695 (0·143)**
LDC→A: Intercept	**−4·139 (0·286)**	**−4·096 (0·114)**		

through this signalling process, in the confining of workers with different productive abilities in different types of jobs.

The results concerning transitions from regular (UDC) jobs reveal that, for young people with a technical school certificate, the previous occurrence of a programme in the public sector with neither formal nor specific training is related to a higher intensity of transition from regular employment to unemployment than other types of programmes (namely, SIVP and apprenticeship, qualification or adaptation contracts): this result may be explained by the fact that regular jobs offered by employers to young people after a training period in the firm have better attributes than the ones offered to young people having just experienced a programme in the public sector, and so that they generate better matches and longer subsequent employment durations. Moreover, a young worker with no experience who was previously in a programme (whatever its type) or in a temporary job and who is currently employed in a regular job moves less frequently to a temporary job than if he was previously unemployed.

TABLE 4.1 (end)

Transition intensities from PEP and OLF states

Variables	Young men without any diploma ($N=672$)		Young men with a technical school certificate ($N=405$)	
	Model A	Model B	Model A	Model B
$PEP \to U$: Intercept	**−2·424 (0·044)**	**−2·668 (0·080)**	**−2·532 (0·139)**	**−2·594 (0·108)**
$PEP \to UDC$: Intercept	**−3·394 (0·210)**	**−3·368 (0·098)**	**−3·094 (0·068)**	**−3·232 (0·121)**
$PEP \to LDC$: Intercept	**−4·501 (0·652)**	**−4·766 (0·111)**	**−4·290 (0·455)**	**−4·328 (0·141)**
$PEP \to OLF$: Intercept	**−5·010 (0·537)**	**−5·976 (0·116)**	**−4·287 (0·286)**	**−4·295 (0·141)**
$PEP \to A$: Intercept	**−4·494 (0·371)**	**−4·612 (0·109)**		
$OLF \to U$: Intercept	**−2·944 (0·094)**	**−2·958 (0·100)**	**−2·943 (0·086)**	**−3·033 (0·133)**
$OLF \to UDC$: Intercept	**−5·018 (0·262)**	**−5·278 (0·118)**	**−4·535 (0·353)**	**−4·756 (0·150)**
$OLD \to LDC$: Intercept	**−5·567 (0·702)**	**−5·789 (0·119)**	**−5·223 (0·577)**	**−5·572 (0·152)**
$OLF \to PEP$: Intercept	**−4·557 (0·454)**	**−4·671 (0·116)**	**−4·810 (0·399)**	**−4·971 (0·152)**
$OLF \to A$: Intercept	**−4·985 (0·283)**	**−5·348 (0·117)**		
α_1	−0·067 (0·263)		−0·021 (0·126)	
α_2	−0·203 (0·311)		0·234 (0·170)	
α_3	**−0·889 (0·078)**		**−1·016 (0·079)**	
α_4	0·316 (0·499)		−0·253 (0·261)	
α_5	0·215 (0·641)		**−0·244 (0·107)**	
α_6	**0·682 (0·350)**			
α_{11}		**−0·592 (0·084)**		**0·259 (0·075)**
α_{21}		**0·258 (0·079)**		−0·114 (0·084)
α_{31}		**−0·357 (0·090)**		**−1·794 (0·139)**
α_{41}		**−0·875 (0·107)**		**−0·302 (0·098)**
α_{51}		**−2·199 (0·119)**		**−0·561 (0·076)**
α_{61}		**0·453 (0·094)**		
α_{12}		0·041 (0·062)		**−0·694 (0·104)**
α_{22}		**−0·682 (0·087)**		**0·645 (0·106)**
α_{32}		**−1·276 (0·104)**		**0·730 (0·121)**
α_{42}		**0·404 (0·083)**		**0·656 (0·118)**
α_{52}		0·155 (0·114)		**0·808 (0·099)**
α_{62}		**0·944 (0·104)**		
μ_1		**−0·319 (0·109)**		**−0·467 (0·137)**
μ_2		**−0·680 (0·112)**		**−0·499 (0·149)**
μ_3		**0·346 (0·112)**		**−4·244 (0·150)**
ω_{11}		**−0·491 (0·070)**		**−0·799 (0·099)**
ω_{12}		**1·592 (0·117)**		**1·550 (0·142)**
ω_{21}		**−0·883 (0·080)**		**−0·741 (0·105)**
ω_{22}		**0·962 (0·101)**		**1·077 (0·120)**
Log-likelihood	−10,536·76	−10,519·93	−5807·58	−5790·77

Notes. Meaning of abbreviations for Table 4.1: QC, AC, App: Qualification Contract, Adaptation Contract, or Apprenticeship Contract.
Remark. In Table 4.1, figures between brackets are standard deviations. Bold type style indicates a 5% significance level while italic type style means a 10% one.

Baseline piecewise-constant intensities of transition from unemployment are not much modified when the distributional assumption on the unobserved heterogeneity terms changes. Intensities of transition from unemployment to regular employment or to temporary employment are decreasing for young men with a very low educational level, while they are constant for young men having a professional diploma. For this last group and at that time (1986–1988), long-term unemployment did not reduce the chances of getting a regular (or a temporary) job: from this viewpoint, long-term unemployment was only unfavourable to the least-educated young workers. Under assumption (11), i.e. when the individual random effects are supposed to be log-normally distributed, the intensity of transition from unemployment to training programmes is constant through the unemployment spell. However, when these random effects are assumed to have a bivariate discrete distribution with two points of support (model B), this transition intensity increases slightly after twelve months: this could be due to a decline of the reservation wage which makes training programmes more acceptable over a longer period of unemployment, or to the fact that subsidized jobs in the public sector (community jobs, for example) are more frequently offered to long-term unemployed people.

Finally, the estimated effects of the time-varying covariate indicating qualification for the UI system through the unemployment spell is sensitive to the distributional assumption concerning unobserved heterogeneity, except in the case of the intensity of transition from unemployment to temporary employment which is lower for low-educated young workers before time of benefit exhaustion.[14] In general, qualification for UI has no effect or a negative effect on the rates of exit from unemployment. However, when young unemployed men with no educational diploma are still qualified for the UI system, they are transiting more intensively to programmes (the corresponding estimating parameter is significant with model B). This last result could be due to an incentive effect resulting from the legislation concerning eligibility rights to the UI system. More precisely, when an unemployed young worker qualified for UI accept to enter into a programme, the UI payment is interrupted during the programme, but the worker keeps his remaining rights to UI if he re-enters unemployment at the end of the programme.

In model A, most of the estimates of parameters a_k associated with the unobserved Gaussian heterogeneity term are not significantly different from zero: according to this model, selection into programmes does not depend on unobservable covariates. On the contrary, estimates of parameters a_{kj} in model B imply that unobservables have significant effects on programme entry. More precisely, estimates of correlations between random heterogeneity terms show that selection into programmes is "negative" for young men without any diploma: this means that, in this subgroup, individuals who are unexpectedly likely to enter programmes are also unexpectedly likely to enter unemployment. At the opposite, selection is "positive" for young men holding a technical school certificate: here, individuals who are unexpectedly likely to enter programmes are also unexpectedly likely to be hired in permanent jobs.

IV.2. *Some useful indicators*

Estimated transition intensities may be used to calculate some summary indicators of the magnitude of programme effects. We concentrate here on the conditional probability that some state k directly follows state j $(k \neq j)$ and on the conditional probability of becoming long-term unemployed, given that a programme has been previously experienced. Given the importance of the self-selection issue in assessing the effects of training programmes, we report estimates of these conditional probabilities after elimination of the effects of unobserved heterogeneity on transitions towards the programmes. For that purpose, we calculate these indicators as expectations of conditional probabilities over the unconditional distribution of the unobserved heterogeneity. Under the assumptions of the model,

14. This result could be explained by a change in the search behaviour of low-educated young workers through their unemployment spell: once they are no more qualified for the UI system, they could be more disposed to accept temporary jobs, which are more frequent but often associated with lower wages.

these expectations may be viewed as the conceptual equivalent of random assignment to the different programmes.

When covariates do not vary during the lth spell in state j, the conditional probability that state k follows state j $(k \neq j)$, given the value $X(\tau_l)$ of individual covariates at time τ_l of entry into the current spell in state j, is equal to

$$\Pi_{k|j}(X(\tau_l)) = \int_{w \in W} \Pi_{k|j}(X(\tau_l), w) f(w) dw, \tag{14}$$

where

$$\Pi_{k|j}(X(\tau_l), w) = \int_0^{+\infty} h_{jk}(u \,|\, X(\tau_l), w) S_j(u \,|\, X(\tau_l), w) du. \tag{15}$$

In equation (14), W (respectively, f) denotes the support of the distribution (respectively, the density function) of the random heterogeneity term w. When w has a discrete distribution, the integral in equation (14) is substituted for a simple sum over the points of support of w. If the origin state j is different from unemployment $(j \neq 1)$, the assumption of time-constant baseline transition intensities implies that

$$\Pi_{k|j}(X(\tau_l), w) = \frac{h_{jk}(X(\tau_l), w)}{\sum_{k' \neq j} h_{jk'}(X(\tau_l), w)}, \qquad j \neq 1. \tag{16}$$

If the origin state is unemployment $(j = 1)$, assumption (10) implies that

$$\begin{aligned} \Pi_{k|1}(X(\tau_l), w) = & \frac{h_{1k}^{(1)}}{\sum_{k' \neq 1} h_{1k'}^{(1)}} [1 - \exp\{-6 \textstyle\sum_{k' \neq 1} h_{1k'}^{(1)}\}] \\ & + \frac{h_{1k}^{(2)}}{\sum_{k' \neq 1} h_{1k'}^{(2)}} \exp\{-6 \textstyle\sum_{k' \neq 1} h_{1k'}^{(1)}\} [1 - \exp\{-6 \textstyle\sum_{k' \neq 1} h_{1k'}^{(2)}\}] \\ & + \frac{h_{1k}^{(3)}}{\sum_{k' \neq 1} h_{1k'}^{(3)}} \exp\{-6 \textstyle\sum_{k' \neq 1} (h_{1k'}^{(1)} + h_{1k'}^{(2)})\}, \end{aligned} \tag{17}$$

where

$$h_{1k}^{(l)} = \exp(\delta_{0k} + \delta_{lk} + \beta'_{1k} X(\tau_l)) v_k, \qquad l = 1, 2, 3, \tag{18}$$

with $\delta_{1k} = 0$ for identification, v_k being alternatively defined by equations (11) and (12). These probabilities are calculated by using ML parameter estimates of the models (11) and (12) for unemployed workers not qualified for the UI system and for workers currently occupied in a regular job. In the case of an unemployed worker who is eligible to the UI system, we have to consider the potential duration T of his eligibility period. For instance, in 1986 in France, if an unemployed worker was employed between 3 and 6 months, 6 and 12 months or more than 12 months during the year preceding his entry into unemployment, the length of his UI elegibility period was 3, 8 and 14 months, respectively. People who were previously employed in a community (TUC) job were generally not qualified for UI once they re-entered unemployment. For example, when the eligibility period is greater than 12 months (for instance, $T=14$ months), the conditional probability that a spell in state k follows directly the current spell of unemployment is equal to

$$\begin{aligned}\Pi_{k|1}(X(\tau_l), T, w) = {} & \frac{h_{1k}^{(1)*}}{\sum_{k'\neq 1}[h_{1k'}^{(1)*}]}[1-\exp\{-6\textstyle\sum_{k'\neq 1} h_{1k'}^{(1)*}\}] \\ & + \frac{h_{1k}^{(2)*}}{\sum_{k'\neq 1}[h_{1k'}^{(2)*}]}\exp\{-6\textstyle\sum_{k'\neq 1} h_{1k'}^{(1)*}\}[1-\exp\{-6\textstyle\sum_{k'\neq 1} h_{1k'}^{(2)*}\}] \\ & + \frac{h_{1k}^{(3)*}}{\sum_{k'\neq 1}[h_{1k'}^{(3)*}]}\exp\{-6\textstyle\sum_{k'\neq 1}(h_{1k'}^{(1)*}+h_{1k'}^{(2)*})\} \\ & \times[1-\exp\{-(T-12)\textstyle\sum_{k'\neq 1} h_{1k'}^{(3)*}\}] \\ & + \frac{h_{1k}^{(3)}}{\sum_{k'\neq 1}[h_{1k'}^{(3)}]}\exp\{-6\textstyle\sum_{k'\neq 1}(h_{1k'}^{(1)*}+h_{1k'}^{(2)*})-(T-12)\textstyle\sum_{k'\neq 1} h_{1k'}^{(3)*}\},\end{aligned}$$

where

$$h_{1k}^{(l)*} = \exp(\delta_{0k}+\delta_{lk}+\beta'_{1k}X(\tau_l)+\gamma_{1k})v_k, \qquad l=1, 2, 3, \tag{19}$$

$h_{1k}^{(l)}$ being defined in (18). Calculations of these probabilities for $0<T\leqq 6$ and $6<T\leqq 12$ are not reproduced here.

Moreover, the probability of becoming long-term unemployed (i.e. to be unemployed for a period greater than 12 months) given the length T of the UI eligibility period is equal to

$$S_1(12|X(\tau_l), T) = \int_{w\in W} S_1(12|X(\tau_l), T, w)f(x)dw, \tag{20}$$

where

$$\begin{aligned}S_1(12|X(\tau_l), T, w) &= \exp\{-6\textstyle\sum_{k'\neq 1}(h_{1k'}^{(1)*}+h_{1k'}^{(2)*})\}, && \text{if } T>12, \\ &= \exp\{-\textstyle\sum_{k'\neq 1}[6h_{1k'}^{(1)*}+(T-6)h_{1k'}^{(2)*}+(12-T)h_{1k'}^{(2)}]\}, && \text{if } 6<T\leqq 12, \\ &= \exp\{-\textstyle\sum_{k'\neq 1}[Th_{1k'}^{(1)*}+(6-T)h_{1k'}^{(1)}+6h_{1k'}^{(2)}]\}, && \text{if } 0<T\leqq 6,\end{aligned}$$

$h_{1k}^{(l)}$ and $h_{1k}^{(l)*}$ being defined in (18) and (19), respectively.

Tables 4.2.a and 4.2.b show that these indicators are very sensitive to the distributional assumption on the unobserved heterogeneity terms. For the subsample of young men with a low level of education, the choice of a bivariate discrete distribution (model B) results in a much higher (respectively, lower) estimate of the expected probability of moving to a permanent job (respectively, to another training programme) at the end of the unemployment spell which follows participation to a training programme. However, the estimate of the expected probability of becoming long-term unemployed is not as sensitive to this specification assumption. For the young male subsample with a technical school certificate, the results are strictly different: the estimate of the expected probability of becoming long-term unemployed is more sensitive to the assumption concerning unobserved components than the estimates of the expected probabilities of transition from unemployment to other

TABLE 4.2.a

Probability of unemployment outcomes according to the state previously occupied
(percentages)
Young men without a diploma

Previous state	First entry	TUC	Other PEP		SIVP		LDC		QC, AC, App		UDC	
Potential duration of UI eligibility (in months)	0	0	3	8	3	8	3	8	8	14	8	14
Probability of transition to												
UDC												
Model without heterogeneity	16·5	12·4	25·0	25·2	17·0	17·8	18·1	20·4	25·6	24·7	43·1	43·9
Model A	17·5	10·4	21·1	22·2	13·8	15·1	18·6	20·6	24·9	25·1	40·3	41·7
Model B	19·0	17·1	31·8	33·8	27·3	29·9	22·4	25·0	50·1	51·3	46·2	48·2
LDC												
Model without heterogeneity	59·7	48·4	35·7	29·7	50·0	40·3	64·7	57·4	17·2	14·0	31·4	27·4
Model A	46·1	43·0	37·8	29·4	51·1	43·8	50·9	45·9	21·9	18·5	25·6	22·4
Model B	47·0	45·8	33·6	28·9	43·1	36·8	48·2	43·0	20·3	17·3	22·8	19·6
PEP												
Model without heterogeneity	11·5	28·5	24·7	30·6	25·2	33·9	8·8	12·7	49·8	55·4	12·7	15·2
Model A	16·7	29·4	24·7	29·8	24·1	31·1	12·8	15·5	44·5	49·1	14·8	17·1
Model B	8·7	15·0	11·8	14·9	12·6	16·5	7·8	20·2	16·9	19·2	8·9	10·6
prob (Unemp > one year)												
Model without heterogeneity	35·9	32·6	44·2	45·7	23·2	26·4	24·4	32·0	23·4	21·4	42·3	44·8
Model A	45·2	30·8	40·7	43·0	17·8	20·7	31·4	36·7	20·7	20·6	43·5	46·1
Model B	34·3	29·8	35·5	41·9	20·8	26·2	28·3	36·1	19·5	22·8	41·2	46·6

TABLE 4.2.b

Probability of unemployment outcomes according to the state previously occupied
(percentages)

Young men with a technical school certificate

Previous state	First entry	TUC	Other PEP		SIVP		LDC		QC, AC, App		UDC	
Potential duration of UI eligibility (in months)	0	0	3	8	3	8	3	8	8	14	8	14
Probability of transition to												
UDC												
Model without heterogeneity	12·2	3·8	10·9	12·7	14·0	16·4	14·2	16·2	12·2	12·7	22·4	23·0
Model A	16·5	4·5	10·5	11·1	15·7	16·6	19·5	18·9	12·6	12·6	21·8	21·5
Model B	19·1	5·0	9·7	9·8	15·3	16·1	23·1	21·4	13·2	13·2	23·9	22·9
LDC												
Model without heterogeneity	42·2	11·6	33·5	27·7	23·5	19·5	52·5	42·7	14·3	12·4	26·1	22·8
Model A	33·1	10·0	35·4	33·1	20·7	19·4	41·8	36·3	13·2	12·2	27·0	25·1
Model B	27·3	8·8	37·9	36·8	19·4	18·7	32·2	29·6	17·3	16·8	21·0	20·0
PEP												
Model without heterogeneity	30·1	74·3	33·3	27·8	41·9	34·9	23·2	8·3	32·6	27·9	12·6	10·8
Model A	33·8	75·4	32·5	26·2	41·8	33·8	12·6	9·5	31·4	26·6	12·5	10·5
Model B	35·9	75·3	27·9	22·1	39·3	32·2	17·8	10·1	28·8	25·4	11·7	9·6
prob (Unemp > one year)												
Model without heterogeneity	21·7	11·4	10·1	10·7	7·4	8·1	11·6	11·6	21·6	19·3	18·7	16·2
Model A	28·7	13·9	11·2	9·9	10·3	9·2	19·6	15·3	22·4	18·8	18·2	14·7
Model B	18·8	7·3	7·3	6·7	5·0	5·1	13·6	10·6	10·1	9·0	12·5	10·1

states. In spite of the high sensitivity of estimates, it appears that the estimates of these expected probabilities vary significantly with the types of programmes previously experienced. For example, for young men without any diploma, the expected probability of becoming long-term unemployed for the ones who were previously participating to a "workplace" training programme (like a qualification, adaptation or apprenticeship contract) is half of the same probability calculated for the ones who were previously participating "courses for the 16-to-25 years old" (called "other PEP" in Tables 4.2) or who enter the labour market for the first time. The efficiency of workplace programmes in the private sector is strengthened by the fact that, for the low-educated people, the expected probability of getting a permanent (UDC) job at the end of the current unemployment spell is much higher if they were previously participating to workplace programmes: on the contrary, this probability is low when they enter the labour market for the first time or when they were previously employed in community jobs (TUC). In terms of these indicators, the benefits of alternating work/training programmes are less pronounced for young men with a higher educational level (see Table 4.2.b). Moreover community jobs reduce significantly their chance of getting a regular job at the end of the current unemployment spell. Indeed this chance is higher for a young man entering the labour market for the first time. However community jobs and programmes characterized by low training levels, such as "courses for preparation to the working life" (SIVP) and "courses for the 16-to-25 years old" (other PEP), are associated with lower expected probabilities of becoming long-term unemployed and with shorter unemployment spells which in turn end up frequently with a re-entry into a training programme: for instance, 75% of unemployment spells occurring after employment in community jobs are directly followed by re-entries into programmes.

Moreover let us notice that, when entering the labour market, young men holding a technical school certificate are more likely to have access to a training programme than less educated young males. So it is clear that participation in training programmes is highly selective. Finally, let us notice that the expected probability of becoming long-term unemployed does not increase significantly with the duration of the period of qualification for UI.

Table 4.3 contains estimates of the expected probabilities of transition from regular jobs according to the state previously occupied. First of all, let us remark that the expected probability of a transition to unemployment is higher for young men previously participating to programmes in the public sector (TUC and other courses) than for those previously participating to alternating work/training programmes in the private sector (SIVP and contracts). On the whole, the expected average duration of a regular employment spell (or equivalently the expected probability that it exceeds one year) is higher when it has been preceded by an alternating work/training programme in the private sector.[15]

V. SUMMARY AND CONCLUSIONS

This analysis has focused on the short-term impact of youth employment programmes set up in France during the 1980's on the labour market trajectories of recipients, especially on durations of their subsequent spells of unemployment and employment. Our study, using non-experimental transition data, has paid particular attention to the possible effects

15. As a referee pointed out, omitting the age covariate may lead in particular to an overestimate of the permanence of employment spells for the sample as a whole.

TABLE 4.3

Probability of transitions from regular (UDC) jobs
(percentages)

Destination state / Previous state	U+OLF	LDC	SIVP+ Contracts	Other courses+ TUC
Unemployment (U)				
N.d.				
Model A	47·8	64·6	39·1	51·9
Model B	41·9	57·4	25·5	50·8
T.c.				
Model A	52·0	54·0	33·4	69·8
Model B	43·3	41·8	30·4	59·3
Temporary jobs (LDC)				
N.d.				
Model A	23·5	3·6	27·4	19·0
Model B	22·7	5·1	29·8	7·1
T.c.				
Model A	26·9	27·9	36·2	17·5
Model B	33·7	25·5	39·0	26·2
Training programmes (PEP)				
N.d.				
Model A	10·8	12·3	12·7	15·2
Model B	8·4	9·1	11·4	11·1
T.c.				
Model A	14·4	7·5	20·9	8·6
Model B	15·5	27·1	20·8	9·5
prob (UDC > one year)				
N.d.				
Model A	28·7	34·9	34·3	20·6
Model B	32·7	36·8	41·4	40·0
T.c.				
Model A	39·9	55·6	51·6	22·2
Model B	36·1	55·5	43·8	21·3

Notes. Abbreviations for education levels: N.d. (no diploma), T.c. (technical school certificate).

of unobserved individual heterogeneity on rates of transition towards programmes, thus capturing the potentially selective nature of training enrolment. A special emphasis has been put on the differential effects of various types of programmes (roughly speaking, workplace programmes in the private sector vs. "workfare" programmes in the public sector), according to the educational level of individuals. Estimates show that:

(a) According to their nature and the amount of training they involve, youth employment programmes have different effects on the recipients' trajectories; for instance, participation in alternating work/training programmes in the private sector increases the intensity of transition from the following unemployment spell to regular employment for young males with a low educational level, while it has no effect on the same transition for young men holding a technical school certificate; at the same time, the experience of a "workfare" programme in the public sector (e.g. a community job) has no effect on the intensity of transition from unemployment to regular jobs for the least educated young people, while it decreases significantly this transition intensity for young men with a vocational diploma; so participation in these programmes may act as a negative signal at higher educational levels; however, for this subgroup of people, community jobs are associated with a lower average duration of unemployment and with a highly probable re-entry into programmes; simultaneously, a regular job preceded by an alternating work/training programme in the private sector has a higher expected duration than a regular job following a community job or a course in a public training centre; moreover, it ends less frequently with a transition to unemployment;

(b) Participation in programmes is highly selective; it depends firstly on the state currently occupied (for instance, for young men holding a technical school certificate, transitions from unemployment to programmes are more frequent than transitions from temporary employment to programmes); it depends also on the educational level of young workers (the least educated ones move less intensively from unemployment to programmes); finally, it depends on past occurrences of programmes, but also on individual unobserved heterogeneity (at least, when we assume that this random heterogeneity follows a bivariate discrete distribution with two points of support); let us notice that we can only detect first-order effects of past programme occurrences[16]; consequently, programme participation has a very short-term impact on individual labour market histories;

(c) The duration of the period of entitlement to unemployment insurance (UI) does not increase the expected duration of unemployment spells; when they are still qualified for UI, the least educated young workers enter programmes more intensively; this could be due to an incentive effect resulting from the legislation on UI. Once again, this result is only verified under the assumption of a bivariate discrete distribution for the unobserved heterogeneity terms.

Obviously many other questions could be addressed. In particular, one could try to examine the effects of exemptions from social contributions as incentives for firms to hire young workers in alternating work/training programmes. One could also try to know if firms substitute these subsidized jobs to regular or temporary ones. These questions are beyond the scope of this study, primarily because they require informations on firms which are not available in the data set we use. Finally, one could be interested in measuring the effects of introducing these programmes on the employment prospects of young workers as a group, and then in discussing the equilibrium effects of such policies. This could be done by estimating displacement effects which result from the fact that a transition into a workplace programme by any one worker affects the job-finding prospects of any other worker by filling a vacancy. The impossibility of ascertaining the importance of such an issue is clearly a limitation of the current research approach.

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16. In additional estimates which are not reported here, we have introduced among covariates affecting transitions from unemployment a dummy variable indicating if the individual has participated to a training programme before the spell preceding entry into the current unemployment spell; this variate appears to have no significant effect on rates of exit from unemployment, while its introduction leaves relatively unchanged the effects of a training period occurring just before the current unemployment spell. However, our test is subject to some criticism: because data contain no information on the participation history preceding the spell which occurred just before the sampled unemployment spell, we restricted the estimation of models with "second-order" effects to subsequent unemployment spells, which are more likely observed for more mobile individuals.

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