

# Unemployment Durations of French Young People: the Impact of Individual, Family and other Factors on the Hazard Rate

Anna Cristina D'Addio<sup>\*</sup>

January, 1998

## Abstract

This paper is concerned with the analysis of the determinants of unemployment durations of French Young People. The data used are extracted from the Enquête Emploi 1990-1992 and the Module Jeunes 1992, both carried out by INSEE. A reduced form approach has been adopted. It is based on the estimation of a discrete-time hazard model which derives from the extension of the Cox model (1972) as in Prentice and Gloeckler (1978). The baseline rate is piecewise constant, it is thus constant within each duration interval of two months. A discrete-time hazard model with unobserved heterogeneity has been estimated too. In it unobserved heterogeneity has been modelled by means of a gamma distribution.

Estimations have been performed separately on men and women durations. Various explanatory variables have been introduced in the analysis; they are significant in most cases, but their effects vary according to the population of reference. The conditions to access the labour market will then seem to be very different for the two groups studied. Only the education level have a positive and significant effect at the same time on the hazard rate of the two subgroups studied. It is also worthwhile to remark that the variables introduced to take account for the date of entry in the unemployment spell, have a significant negative effect on the probability of leaving unemployment both for men and women. The hazard rate seems very sensitive to the economic situation, the groups the less attached to the labour market seem to be the more sensitive to the economic situation.

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<sup>\*</sup>IRES and Core, Department of Economics, Université Catholique de Louvain, Louvain-la-Neuve, Belgium. E-mail daddio@ires.ucl.ac.be

<sup>†</sup>I wish to thank I. Bardoulat, G. Bijwaard, B. Cockx, J. Devaux, T. Magnac, M. Mouchart, D. Powers, G. van den Berg and especially S.P. Jenkins, University of Essex, for all useful help and suggestions. The author is solely responsible for any error in the present paper.

## 1. Introduction

Unemployment, in general, and more particularly unemployment of the youth is a phenomenon that holds the attention of all Western countries.

It is a research topic that one can find in several works and that has been studied using different approaches (see Devine and Kiefer, 1991). Its empirical description started with works of Lancaster (1979) and Lancaster and Nickell (1980) and developed through econometric duration models. Indeed, unemployment duration has been one of the most extensively studied issues in the U.S. and some European countries. For instance, in the papers written in France on this subject, one finds diversities based both on the methods and implicit assumptions to the methods, and on the kind of the data used.<sup>1</sup>

In France the increase in total unemployment since 1975 was accompanied by a considerable increase in the number of the long-term unemployed. A great part of this rise may be explained by the substantial lengthening of average unemployment durations rather than the increase inflows into unemployment (Moreau and Visser, 1989). It would thus seem that the rise in the unemployment rate does not result mainly from more frequent entries but from reclassification difficulties much more important (Thélot, 1988). Relative to the unemployment of the young persons, it must be noticed that it raised considerably too in the last twenty years.

As to the unemployment of the youth, it must be said that it is among the top policy issues of all Western European countries. Various analysis were undertaken on this topic. Some authors have used the individuals' labour market histories to assess the effects of specific policy programs (see for apprenticeships and training programs Bonnal, Fougère and Sérandon, 1997; for training programs Magnac, 1996). Others have studied their unemployment durations in order to provide answers to some specific questions (see Fougère, 1986; Moreau and Visser, 1989; Abbring, van den Berg and van Ours, 1996) among which it is necessary to remember the studies that have focused on the distinction between state dependence and unobserved heterogeneity (Magnac, 1996) or between duration dependence and unobserved heterogeneity (see van den Berg and van Ours, 1996).

Fitting in this last framework of analysis, this paper focuses on the effects of individual, family, calendar time and other factors on the unemployment durations of young persons and, at the same time, tries to assess their differential effects between men and women. Moreover it aims at checking if heterogeneity between the youth is at the origin of different conditions to access to the labour market.

The empirical analysis uses the method discussed in Prentice and Gloeckler (1978). Two discrete-time (grouped duration data) proportional hazard regression models have been estimated. They are: (1) the Prentice-Gloeckler (1978) model; and (2) the Prentice-Gloeckler (1978) model that incorporates a gamma mixing distribution to capture unobserved individual heterogeneity, as suggested in Meyer (1990). The exposition of the models draws on Stewart (1996) and Jenkins (1997).

The paper is organized as follows. The next section presents some features of the French labour market. Section 3 describes the sample and the data used for the analysis, in addition some descriptive statistics are presented in order to give a general idea of the available information. Methods of estimation are presented in section 4. Section 5 will be devoted to a discussion of the main findings. Some conclusion are

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<sup>1</sup>See for instance Bonnal and Fougère, 1990; Florens, Gerard-Varet and Werquin, 1988; Thélot, 1988; Cases and Lollivier, 1993.

drawn in section 6.

## 2. The Youth French Labour Market

In France during the twenty last years the fight against young people unemployment has become one of the top priority of all the governments. The unemployment of the youth is indeed not desirable both from an economic and social point of view. In most cases the young unemployed do not have any experience on the labour market and their exclusion from this one, is likely both to reduce the human capital and knowledge they acquired during their studies.

Since 1983 the unemployment rate of the youth seldom has been below the 20% level even if it knew a slight fall in 1986. At the end of 1995 it reached 27.3% of the active population, and 9.7% of the population aged 15-25 (Eurostat, 1997).

Other countries know such a situation. Unemployment among the under 25s ranged from 5.6% in Austria, to 33.2%, 38.2% and 42% respectively in Italy, Finland and Spain (Eurostat, 1997).

[Table 2.1]

Persistence in France of a such high unemployment rate of the young people is all the more astonishing since their rate of schooling did not stop increasing these last years.<sup>2</sup> People having no qualification passed from 49.8% of the population in 1962 to 21% in 1990, the number of those having a baccalauréat -BAC- raised from 5.8% in 1962 to 13.1% in 1990 and finally the share of those having a level of education higher than the BAC raised from 2.7% in 1962 to 15.2% in 1990 (Bruno and Cazes, 1997).

Moreover on the one hand during the same period many and diversified policies and supplementary programs were conceived to make the insertion of the youth on the labour market easier<sup>3</sup>. On the other hand demographic reasons did not contribute to increase unemployment of the young people, indeed the total population of the youth relative to the overall population have been appreciably decreasing since the beginning of the Seventies.

It seems however that unemployment is almost an obliged step for the majority of the youth coming out of the schooling system, the direct access to employment being increasingly rare.

As to the composition of young people unemployment, it must be noticed that the higher share in it is represented by non-qualified persons as shown in the following table.

[Table 2.2]

Nevertheless the number of qualified young people as well as their share in unemployment do not cease growing as illustrated in table 2.2 meaning that they encounter a lot of difficulties too, to enter the labour market. This may be due on the one hand to the fact that the labour market demand for qualified people has not grown in a way sufficient to absorb the increasing flow of qualified young people. On the other

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<sup>2</sup>The share of 18-years old in education and non-active, attained in 1995 in France 84% (Eurostat, 1997).

<sup>3</sup>For a synthesis of policies and their history see Bonnal, Fougère and Serandon, 1997; Lechene and Magnac, 1995.

hand to the inadequacy between the training and schooling system and the real needs of the Economy (Sneessens, 1994).

Still it should be stressed that young people often know fixed term contracts intersected with unemployment spells: the difficulty of finding a stable job is then another characteristic of the situation of the young people on the labour market. This is illustrated by the fact that average unemployment durations are lower for the youth than for the adults whereas the cumulated durations are higher for the former (Bruno and Cazes, 1997).

### 3. The sample and the variables

#### 3.1. The data base

Available data for the analysis of unemployment durations come from both the “Enquête Emploi” 1990-92 and a special survey (led in 1992) that reports some additional information on the young people. This latter survey takes the name of “Module Jeunes”. Both surveys were carried out by the *Institut National de la Statistique et des Etudes Economiques* (INSEE.).

Data come from a retrospective survey, indeed the data source is a biographical investigation where at the time of the interview one endeavors retrospectively to recall the trajectory of an individual. This way of acting has surely the advantage to allow to recall long histories, but has also a major disadvantage: the lack of memory of the questioned individuals may generate errors in the observations and by there prohibit very precise observations.<sup>4</sup>

In this survey 4237 households are present at all the dates, moreover an individual aged between 18 and 29 in 1992 has to belong to them. These young persons are interviewed on their occupational histories since they were 16, and they are asked to give more details about family and individual status. Interviews were carried out on three dates: January 90, March 91 and March 92. The available sample is made of 5824 young individuals.

The “Enquête Emploi” records the situation of the individual at the date of the survey and, moreover, his/her principal occupation, on a monthly basis, in the previous year. Individuals’ statutes are then rebuilt over the period going from January 1989 to March 1992<sup>5</sup>. The “Module Jeunes” also reports the main occupation<sup>6</sup> of the youth since they were 16 till December 1988.

Data are multistates and multiepisodes. By multistate, one understands data which provide information on the whole trajectory of the individuals on the labour market during the observation period: individuals can thus pass through various states. Six states are distinguished in the data base. They are: 1. Permanent Employment, 2. Fixed Term Employment, 3. Training, 4. Unemployment, 5. Education, 6. Out of the labour force. With the term multiepisode it is meant that the individual can know several episodes of the same type (for example he/she can have experienced various unemployment spells over the observation period).

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<sup>4</sup>See Fougère, Florens, Kamionka and Mouchart (1995); Magnac and Visser (1996).

<sup>5</sup>For a comment on the coherence degree between information in the “Module Jeunes” and the “Enquête Emploi” see Magnac, 1995.

<sup>6</sup>Where one understands by “main occupation” the longest episode spent in a particular state of the labour market over a given period: for the Enquête Emploi it is one month, for the Module Jeunes it is one year.

To form the sample used in the empirical analysis only the individuals who have experienced at least one unemployment spell have been selected. This selection turns out in a sample of 2137 unemployment spells, 1079 of which experienced by young men and 1058 by the young women, individuals being respectively 694 (men) and 685 (women). The distribution of the unemployment spells by gender is reported in the following table.

[Table 3.1]

I have thus taken as unit of analysis unemployment spells rather than individuals. This amounts to make the implicit assumption that multiple durations of the same individual are independent from each other.

It is assumed that one spell ends when the individual leaves the state he occupies to enter another one (for instance an unemployed individual can find a stable employment, follow a training course, etc.) otherwise the spell is right censored. In econometric duration models right censoring is usually modelled through a dummy variables that takes on the value 1 if an exit is observed and 0 otherwise.

Due to methodological reasons left-censored spells<sup>7</sup> have been discarded from the sample.

### 3.2. Preliminary description of the sample

In the Module Jeunes various detailed information on the young people are available. Relative to family characteristics it is known for example if the mother and the father were unknown, if they died, if they divorced, their level of education the nationality of the father, the number of brothers and sisters. As to the individual factors, one knows the age of the young people, their level of education, if they had health problems in the childhood, etc. Unluckily data on benefits and incomes are not available in the data base so that they can not be used in this study.

To study the differential effects of these factors on men and women's durations, I have performed the estimations separately on the two subgroups' durations.

To summarize the variables used in the empirical analysis, and to give a preliminary idea on the information available in the survey some descriptive statistics are reported in the following table.

[Table 3.2]

The average unemployment duration of all men's spells is equal to 5.36 months, while the average duration of only completed spells (for which the censoring indicator takes the value 1) is equal to 4.59 months. Relative to the sample of women it must be noticed that the average duration of all spells is equal to 6.79 months, while the average unemployment duration of the sole completed spells is equal to 5.92 months. It should then be stressed that the average duration of unemployment spells is higher for women than for men.

Anyway it must be noticed that the computation of the average duration of an episode of unemployment neglects the fact that a part of the unemployment spells (and precisely those that are still in hand at the end of the survey) are right-censored so that their real duration is not known. This leads then to underestimate the average unemployment durations, for this reason the use of the median duration computed

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<sup>7</sup> That is to say spells that were in hand in January 1989 (at the beginning of the survey).

using the Kaplan-Meier estimator is likely to be more appropriate. It is equal to 4.76 months for men and to 6.59 months for women.

## 4. Methods of estimation

### 4.1. Introduction

The empirical analysis in this paper uses the hazard function. The hazard rate represents then the instantaneous probability of leaving a particular state (here unemployment) at time  $t$  conditional to not having left till the moment immediately before<sup>8</sup>.

Before performing the multivariate analysis, unemployment durations of men and women have been compared using the Kaplan-Meier (1958) survival rate. The rate of hazard of the two groups has also been estimated using life tables method as in Krakauer and Stewart (1991). Both these estimators are non-parametric.

These estimates may help to have a preliminary idea on the shape of the hazard function but they do not provide very precise information due to the non control of other correlated variables. It would be possible to control for the observed differences among individuals by performing estimations for each subgroups. Sample size for each subgroup easily becomes too small to yield any robust estimates.

### 4.2. A discrete-time hazard model

The model used to represent the conditional probability of leaving unemployment is of the proportional hazard form (Cox, 1972). More precisely it is a discrete-time (grouped duration data) hazard model as in Prentice and Gloecker (1978).

The continuous proportional hazard function writes

$$\lambda(t|x_i) = \lambda_0(t) \exp(X'\beta)$$

The hazard function is thus related to a set of explanatory variables  $X$ , that may be either time-invariant or time-dependent, and to the “baseline” hazard rate  $\lambda_0(t)$ . The main feature of this model in contrast to parametric models, is that the baseline hazard is not constrained to belong to a specified parametric family, is indeed arbitrary and not chosen a priori.<sup>9</sup>

In the above formulation it has been assumed that time is a variable that can be observed in a continuous way. Although the models in continuous time can often represent a reasonable hypothesis, in the reality time is mostly observed in discrete units (for instance durations are reported monthly). The use of discrete-time models is then likely to be more correct.

One of the main advantages of the model of Prentice and Gloecker (1978) is that it provides computationally feasible estimator even in presence of many ties (i.e. equal durations for different observations) and it allows easily to introduce in the analysis as well time-varying covariates as unobserved heterogeneity.

Let us suppose that duration data are grouped in  $j$  intervals with the  $j - th$  interval defined as  $[a_{j-1}, a_j]$ . The hazard in the  $j - th$  interval is defined in terms of the survivor function as (see Jenkins, 1997)

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<sup>8</sup>For a description of tools used in econometric duration models see Cox and Oakes (1984), Kalbfleish and Prentice (1980). See also Kiefer (1988), Blossfeld, Hamerle and Mayer (1989), Lancaster (1990), Florens, Fougère and Mouchart (1996).

<sup>9</sup>To compare the results obtained when imposing a specific shape to the hazard function see D’Addio (1996, 1997).

$$h_j(X_{it}) \equiv \Pr\{T \in [a_{j-1}, a_j) | T \geq a_{j-1}\} = 1 - \frac{S(a_j; X_{ij})}{S(a_{j-1}; X_{ij-1})}$$

If the covariates are constant within each interval the survivor function writes:

$$S(a_j, X_i) = \exp\{-\exp(X_i' \beta + \gamma_j)\}$$

where

$$\gamma_j = \ln \int_{a_{j-1}}^{a_j} \lambda_0(u) du.$$

The  $S(a_j, X_i)$  has the form of the survivor function of an Extreme Value random variable. The  $\gamma_j$  ( $j = 1, \dots, k$ ) can be treated as parameters to be estimated along with  $\beta$  (Stewart, 1996).

The sample log-likelihood can be written in terms of the hazard function (Jenkins, 1997)

$$\log L = \sum_{i=1}^n \left\{ \delta_i \log \left\{ h_{t_i}(X_{it_i}) \prod_{s=1}^{t_i-1} [1 - h_s(X_{is})] \right\} + (1 - \delta_i) \log \left\{ \prod_{s=1}^{t_i} [1 - h_s(X_{is})] \right\} \right\}$$

where it has been assumed (to simplify notation) that all intervals are of unit length (Jenkins, 1997; Stewart, 1996) so that the duration for each person  $i$  corresponds to the interval  $[t_i - 1, t_i]$ ;  $\delta_i$  is the censoring indicator that will take the value 1 for completed spells and 0 for right-censored spells. The number of intervals comprising a spell is defined to include the last interval within which the person is observed.<sup>10</sup> Thus a recorded value of  $t_i$  implies  $T_i \geq t_i$  if  $\delta_i = 0$  (Stewart, 1996).

The discrete-time hazard in the  $j$ -th interval is given by:

$$h_j(X_{ij}) = 1 - \exp[-\exp(X_{ij}' \beta + \gamma_j)] \quad (4.1)$$

In the empirical analysis  $\gamma_j$  is constant within two months intervals up to the 26th month and constant thereafter. This specification of the baseline hazard has been chosen on the one hand because the number of spell completed in the last duration intervals is very little, on the other hand because it allows a certain degree of flexibility as to duration dependence specification.<sup>11</sup>

Discrete hazard models have an appealing relationship to binomial model as already noticed in Allison (1982), Kiefer (1990) and Jenkins (1995). Each individual or each spell may be seen as contributing  $k_i$  observations, one for each interval  $j$  entered. This amounts to form a sample of size  $N = \sum_i k_i$  observations. Then a new indicator variable  $y_{it} = 0$  is defined for all spell months; for exitters  $y_{it} = 0$  for all months except for the one in which the spell is completed (Jenkins, 1995). For instance a completed spell of 3 months contributes a sequence of three observations coded 0,0,1. The log-likelihood can be rewritten as:

$$\log L = \sum_{i=1}^n \sum_{j=1}^{t_i} \{y_{ij} \log h_j(X_{ij}) + (1 - y_{ij}) \log [1 - h_j(X_{ij})]\}$$

<sup>10</sup>see Stewart (1996), Jenkins (1997).

<sup>11</sup>see Hujer, Maurer and Wellner (1996).

that is the log-likelihood for the regression of dichotomous dependent variables. More particularly the log-likelihood is the same as the one for a generalized linear model of the binomial family with complementary log-log link (see Allison, 1982; Jenkins, 1995). Indeed the above equation (4.1) may be solved to yield the so-called complementary log-log function:

$$\log[-\log(1 - h_j)] = \gamma_j + X'_{ij}\beta$$

where  $\beta$  is the same as in

$$\log \lambda(t|X_i) = \log \lambda_0(t) + (X'_i\beta)$$

This implies that discrete-time estimates based on (4.1) are also estimates of the underlying continuous-time model (see Allison, 1982).

#### 4.3. A discrete-time hazard model with unobserved heterogeneity

A priori, it is very important to estimate the hazard function on homogeneous populations. In the model presented above it is assumed that all the differences existing among individuals can be explained by the set of covariates, that is to say by the set of observed characteristics. In the reality, it is not possible to observe all the factors suitable for differentiate individuals. These characteristics, that are not observed, take the name of “unobserved heterogeneity”. As it has been noticed in various studies (see Elbers and Ridder, 1982) the lack of control for heterogeneity may lead to spurious duration dependence and to bias in the parameter estimates of the hazard function. Indeed if the population is made of groups with different distribution of duration, the risk is to show a false decrease in the hazard function (Gourieroux, Pradel, Fourgeaud, 1990).

In the Mixed Proportional Hazard model a random variable is introduced to capture unobserved heterogeneity. The usual way to do this is to specify (see Meyer, 1990, 1995; Stewart, 1996; Jenkins, 1997)

$$\lambda_i(t|x, \varepsilon) = \lambda_0(t)\varepsilon_i \exp[X'\beta] = \lambda_0(t) \exp[X'\beta + \log(\varepsilon_i)]$$

where  $\varepsilon_i$  is a positive-valued random variable with density  $f_\varepsilon(\varepsilon)$ . If  $\varepsilon$  is assumed to have finite mean, it can be assumed that  $E(\varepsilon) = 1$ . (Stewart, 1996)

The Survivor function conditional on  $\varepsilon$  is now

$$S(t|x, \varepsilon) = \exp[-\varepsilon \exp(X'\beta + \gamma_j)]$$

and the unconditional is

$$S(t|x, \varepsilon) = \int_0^\infty \exp[-\varepsilon \exp(X'\beta + \gamma_j)] f_\varepsilon(\varepsilon) d\varepsilon$$

A choice of density for  $\varepsilon$  is then required to enable the calculation of the log-likelihood.

An intriguing problem that raises when modelling unobserved heterogeneity is related to the choice of its distribution (see Heckman and Singer, 1984; Narendranathan and Stewart, 1993; Stewart, 1996). The most commonly used parametric mixing distribution since Lancaster (1979) has been the Gamma distribution, primarily for mathematical convenience. This distribution has been used in this study.



Its density is given by

$$f_{\varepsilon}(\varepsilon) = \frac{\theta}{\Gamma(\alpha)} (\theta\varepsilon)^{\alpha-1} e^{-\alpha\varepsilon}$$

where

$$\Gamma(\alpha) = \int_0^{\infty} x^{\alpha-1} e^{-x} dx$$

The expected value and the variance of a gamma distributed random variable are

$$E(\varepsilon) = \frac{\alpha}{\theta}; \text{ and } Var(\varepsilon) = \frac{\alpha}{\theta^2}$$

In order to meet the assumption  $E(\varepsilon) = 1$  it must be  $\theta = \alpha$  and then

$$f_{\varepsilon}(\varepsilon) = \frac{\alpha}{\Gamma(\alpha)} (\alpha\varepsilon)^{\alpha-1} e^{-\alpha\varepsilon}$$

and  $Var(\varepsilon) = \sigma^2 = \alpha^{-1}$ .

The Survivor function can be written as

$$S(t|x) = [1 + \sigma^2 \exp(X'\beta + \gamma_j)]^{-\frac{1}{\sigma^2}}$$

and the discrete-time hazard function in the  $j - th$  interval is given by

$$h_j(X_{ij}) = 1 - \exp \left\{ -\exp(X'_{ij}\beta + \gamma_j + \log(\varepsilon_i)) \right\}$$

The log-likelihood (Jenkins, 1997) writes

$$\log L = \sum_{i=1}^n \log \{ (1 - \delta_i) A_i + \delta_i B_i \}$$

where (Jenkins, 1997)

$$A_i = 1 + \sigma^2 \sum_{j=1}^{t_i} \exp [X'_{ij}\beta + \gamma_j]^{-\frac{1}{\sigma^2}}$$

$$B_i = \begin{cases} \left[ 1 + \sigma^2 \sum_{j=1}^{t_i-1} \exp [X'_{ij}\beta + \gamma_j] \right]^{-\frac{1}{\sigma^2}} - A_i & \text{if } t_i > 1 \\ 1 - A_i & \text{if } t_i = 1 \end{cases}$$

$\delta_i$  is the censoring indicator that takes on value 1 for completed spells and 0 otherwise,  $\gamma_j$  is the duration parameter,  $\sigma^2$  is the variance of the gamma-distributed random variable as supra defined.

## 5. Determinants of Youth Unemployment Durations

### 5.1. Some Preliminary Indications

Unemployment durations respectively of young men and women have been initially compared using the Kaplan-Meier (Kaplan and Meier, 1958) survival rates as shown in the following graph

[Fig. 5.1]

A log-rank test (Mantel, 1966) has been performed to compare the survivor functions of the two groups. This test is based on the assumption that the survivor functions of the subgroups to be analyzed do not differ and are asymptotically  $\chi^2$  distributed with  $k - 1$  degrees of freedom,  $k$  being the number of subgroups. The log-rank statistic stresses the differences between the two groups, it is significant with the value of 26.65 and one degree of freedom (significance level 0.05).

The non-parametric hazard rate of the two groups has been plotted in Fig. 5.2. The hazard function gives some indications of non-monotonicity. However the roughness of the data does not rule out multi-modality of the hazard.

[Fig. 5.2]

These estimates allow to point out at some differences between men and women duration distributions. Given that the sample size of the two subgroups was big enough, estimations have been performed separately on the subgroups' durations, the target being to assess the different impact of individual, socio-demographic factors on them.

Both the estimators described till now are non-parametric, they do not allow to take account for either observable or unobservable heterogeneity. To study the effects that observed factors can exert, a multivariate analysis have been then applied.

In order to estimate the hazard function both the baseline rate and a vector of covariates must be specified. The covariates introduced will be described in the next section. As to the baseline rate, it has been defined through a set of dummy variables, one for each two months till the 26th months and constant thereafter. The main feature of this kind of function (also known as piecewise constant hazard rate) is that it is constant in each interval but may vary from one interval to the other. The first interval is used as the reference level. After the 13th duration interval (that is to say after the 26th month) the number of observations is too small to use a two-months dummy. The last interval then groups durations from month 27 to month 37 and 36 respectively for men and women.

The use of a proportional hazard model allows for an easy interpretation of the estimated parameters: if the sign is positive the effect on the hazard rate will be positive (shorter durations) otherwise it will be negative (longer durations).

Turning to the results of the models with and without unobserved heterogeneity, it must be noticed that they show strong differences (at least for men) in the significance of the baseline dummies estimates. Indeed for men there is evidence of significant negative duration dependence (i.e. the probability of leaving unemployment decreases with duration) in the model without unobserved heterogeneity, while in the model where it has been introduced the baseline dummies estimates are no longer significant.

This result makes clear the necessity to control for unobserved heterogeneity, indeed to fail its control may lead to formulate false conclusions on the shape of the hazard function.

However, it must be noticed that unobserved heterogeneity seems to be non significant in this context, the model without unobserved heterogeneity could be then preferred.

Different results as to unobserved heterogeneity were found as well in van den Berg and van Ours (1996) as in D'Addio (1997). In these studies, the authors found substantial evidence of unobserved heterogeneity. Different reasons may be at the

origin of such a difference. First of all it must be said that in the study of van den Berg and van Ours (1996) observed individual characteristics are not introduced in the analysis due to the non-availability of such an information. Secondly data used in van den Berg and van Ours (1996) are administrative (they come from the ANPE - *Agence Nationale Pour l'Emploi*) and differ in many respects from those of the INSEE. Thirdly it must be noticed that in the study of D'Addio (1997) the baseline hazard rate was specified as to belong to a parametric family, in the present study the hazard function is on the contrary very flexible and semi-parametrically estimated.

Referring to the covariates introduced in the analysis, their signs and the significance of their parameters are the same in the two models.

The results of the estimations are reported in the following tables.

[Table 5.1]

[Table 5.2]

## 5.2. Individual Characteristics

In this class of factors I have introduced the age of the individual, his(her) level of education and finally whether he/she has followed a technical kind of schooling.

Relative to the age of the individual, it is here about the age of the youth in 1992: thus it is not a time-varying variable. The age can have ambiguous effects on the hazard rate. On the one hand, in general, if it is considered that the age can be used to account for the experience, one should expect that the older is the individual, the easier is for him to be engaged because of the experience he(she) has acquired. On the other hand one may have some doubts about the truthfulness of such a principle: an older unemployed will have more difficulties to reclassify himself on the labour market. The effects of the age on the hazard rate could thus be difficult to establish.

As shown in tables 5.1 and 5.2 the negative sign of the age coefficient, and the fact that it is significant (at least relative to young men durations) show that the older is the individual, the weaker is the probability of leaving unemployment. An older individual (also among persons aged between 18-29) will have then more difficulties to re-enter the labour market. This kind of effect seems rather robust, indeed it appears in various studies in a more or less significant way (Cases and Lollivier, 1994; Bonnal and Fougère, 1990; Gérard-Varet and al., 1990; Magnac, 1996; van den Berg and van Ours, 1995).

Referring to the level of education, one should expect that the higher it is, the higher is the probability of leaving unemployment. In the survey the level of education is expressed in terms of "theoretical age of end of studies". Each value of this variable corresponds thus to the age at which individuals left the schooling system.<sup>12</sup> Even if the compulsory schooling was fixed at 16 years over the observation period, this variable takes on lower values. A closer analysis of those cases revealed that they correspond mostly to individuals whose father is of non-European nationality. The few cases remaining, refer to individuals having known serious health accidents that could have disturbed the normal course of their studies.

Looking at tables 5.1 and 5.2 it can be said that the sign of the estimated coefficient allows to affirm that the higher is the education level, the higher is the probability of leaving unemployment. This is verified, at the same time, for men and for women.

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<sup>12</sup>Relative to this variable I have to face a problem of missing values. The missing information has then been rebuilt using a procedure suggested to me by Bart Cockx. For details on the procedure followed see D'Addio (1997a).

However it must be noticed that even if the education level has been growing for the last thirty years, the share of qualified young people in the total unemployment of the youth does not stop increasing (see Section 2).

To evaluate the effect of a technical kind of schooling an indicator variable has been introduced in the model. Its effect cannot be a priori determined, indeed this variable covers various realities as for the level of education attained.

By observing tables 5.1 and 5.2 one sees that the fact of having followed a technical kind of schooling has a significant impact only on the hazard rate of young women. It seems indeed that the fact of having had a technical formation increases their average unemployment durations. For men the sign of the coefficient is on the contrary positive, even if not significant. A similar result was found in the study of Moreau and Visser (1989). These authors noticed that men having followed a technical kind of schooling had a higher probability of leaving unemployment.

It is important to remark that these results already allow to have a preliminary idea on the factors which can exert an impact on unemployment duration. Moreover it should be stressed that the effects are not equal respectively on men and women's durations.

### 5.3. Socio-demographic characteristics

For young unemployed, family situation is likely to affect their job-search efforts. Relative to family status various information are available in the French Labour Survey, for instance it is known if the father and the mother were unknown, if they died, if divorced, their nationality, their level of education, the number of members of which the family is composed. All these variables were introduced in previous estimations. Due to the lack of statistical significance I have discarded most of them, keeping only the significant ones, the parameter estimates being substantially equal after the omission of the other variables.

Included family status variables in this study are the French nationality of the father and the fact of belonging or not to a large family. Still the need of seeing whether the urban environment exerts an effect on the probability of leaving unemployment justifies the introduction of such an information in the present study. The fact of living in a more or less dynamic environment may be a decisive factor for leaving unemployment.

Referring to the father's nationality, it arises from several studies (see Bonnal and Fougère, 1990; Magnac, 1996) that a relationship between the nationality of the individuals and the probability of leaving unemployment exists. By observing table 5.1 and 5.2 it can be noticed that individuals whose father is French nationality have a higher probability of leaving unemployment. Moreover, this is verified at the same time for young men and women, even if in a more significant way for the former.

Relative to the second variable related to family status, it must be said that the structure of the family could play an important role. With the term "large family" it is meant a family in which the number of children is equal or higher than tree. This variable was built by using the information (reported in the survey) about the number of brothers and sisters of the young individual. From tables 5.1 and 5.2 it derives that there is a negative relation between the hazard rate of women and the structure of the family. The larger is the family, the weaker is thus the probability of leaving unemployment. Relative to men it is worthwhile to remark that the direction of the relation is inverted, even if not significant, it seems that the larger is the family,

the higher is the probability of leaving unemployment. Different reasons could explain such effects: both family incomes and cultural factors could be useful in this respect.

As to the environment in which the young individuals live, I have introduced a variable that contains this information: more precisely it states if the young person lives in Paris or elsewhere in France. As shown in tables 5.1 and 5.2 the fact of living in Paris has a positive and significant effect only on the hazard rate of the young women.

These results show that human, cultural and geographic environment is an important factor for the insertion of the youth on the labour market. In particular the family structure seems to be crucial to describe the behaviour of the young people on the labour market. However owing to the fact that information on family resources is missing, it is not possible to distinguish the effects related purely to the family structure from those related to income levels.

#### 5.4. Other factors

Some other variables have been introduced in the model in order to take into account further observed differences among young individuals. They are: three variables which state the year of entry in the unemployment spell (and thus capture calendar time effects), and two variables that describe the status of the individuals prior to the unemployment spell, particularly if the individuals entered the unemployment spell right after either having exited the schooling system or having had a training spell.

As shown in tables 5.1 and 5.2 the year during which the unemployment spell began is very important. Indeed, the fact of having entered the unemployment spell in the years 1990, 1991, 1992 (year 1989 being then the reference) has a strong negative effect on the hazard rate. The hazard rate thus seems very sensitive to the economic situation and in particular to the recession starting in 1991 in France. This result confirms, as many other studies have shown, that the groups the less attached to the labour market are the more sensitive to the economic situation.

It must be still noticed that entering unemployment right after the end of the studies does not make easier to leave it. The direction of the effect is equal for the two groups, but it is significant only for men.

Relative to the last variable that states if the young person has followed a paid training course prior to enter the unemployment spell, it must be said that its coefficient could be interpreted as a measure of the efficiency of the training course and particularly of their capacity to insert young individuals on the labour market. By observing tables 5.1 and 5.2 it should be noticed that the effect on the hazard rate seems to be negative at the same time for the two groups. However the parameter estimate is not significant. As to the negative sign of the coefficient, it could rise doubts about the inserting capacity of the training courses and their effects (see Magnac, 1996).

## 6. Conclusion

This paper aimed at the analysis of the factors suitable for having an impact on unemployment duration of french young people.

In order to assess their differential effects between men and women, estimations have been performed separately on the two subgroups' durations. Looking at the graphs where the hazard function has been plotted (see Fig. 5.2), it can be noticed

that the probability of leaving unemployment is almost always lower for women than for men. This function has been estimated in a non-parametric way so that observed and unobserved characteristics are not taken into account.

The multivariate analysis based on the estimation of a proportional hazard function and more particularly of its discrete-time version, gives some interesting results, as well in the formulation without as in the one with unobserved heterogeneity.

Some factors have a significant positive effect on the unemployment durations of the two populations studied here. It is the case of the education level and of the father nationality. It can be noticed then on one hand the higher is the level of education, the higher is the probability of leaving unemployment. On the other hand the fact of having a father of non-french nationality seems to increase average unemployment durations.

It is worthwhile to notice that the year in which the unemployment spell began has a strong impact on the unemployment durations. The hazard rate is indeed very sensitive to the economic situation and moreover to the recession started in France in 1991. As shown in many other studies, the groups the less attached to the labour market are the more sensitive to the economic situation.

Some factors having a significant effect on women's unemployment durations have none on men's ones. It is the case of the fact of having followed a technical kind of schooling, of the geographical environment and finally of the fact of belonging to a large family and finally of living in Paris.

Even if in this study unobserved heterogeneity does not seem to be highly significant (that is likely to be due to the very flexible baseline hazard used), it is clear that to fail to control for it may lead to some false conclusions on the shape of the hazard function. Looking at table 5.1 one realizes that in the model without unobserved heterogeneity there is evidence of negative duration dependence, at least for the first twelve months, as well for men as for women (even if it is significant only relative to men). Table 5.2 (in which the results of the model with unobserved heterogeneity are reported) offers a different picture of the situation: most of the baseline dummies are no longer significant.

To be able to distinguish between duration dependence and unobserved heterogeneity is very important, primarily from a policy point of view. In the case of negative duration dependence, when discouragement effects are likely to be present, a policy could be oriented towards preventing workers becoming long-term unemployment (see van den berg, van Ours, 1996). When unobserved heterogeneity is important, it could be useful to observe the characteristics of people flowing into unemployment in order to concentrate on those with bad factors.

In general it must be said that the factors which seem to reduce average unemployment durations of young men are the French nationality of the father, a lower age, a higher level of education, the fact of not having started the unemployment spell in a recession period.

Relative to young women the most favorable factors are the fact of not belonging to a large family, the French nationality of the father, a higher level of education, the fact of not having followed a technical kind of schooling, to live in Paris, having started the unemployment spell in a favorable economic period.

Most of the factors introduced in the analysis have indeed a different effect on the hazard rate of the two groups. These findings confirm the necessity of studying them separately when trying to characterize their unemployment durations, above all taking information on family structure and on calendar time into account.

# Appendix: Tables and Graphs

## Description of the Variables

### *a. Baseline Dummies*

1.  $\gamma_2$ - $\gamma_{13}$ : baseline dummies defined within each two months interval
2.  $\gamma_{14}$ : baseline dummy covering the interval going from the 26th month to the 37th and 36th month respectively for men and for women

### *b. Individual Factors*

3. Individual's age in 1992 [18,29];
4. Level of education of the individual; it is expressed in terms of theoretical age of end of studies and takes on values in the interval [10,29].
5. Dummy variable on the missing values in the level of education;
6. Technical Education (1=Yes);

### *c. Socio-demographic factors*

7. Father Nationality (1=French);
8. Large Family: where the total number of children is greater or equal than 3 (1=Yes);
9. Region of residence (1=Paris; 0=elsewhere in France)

### *d. Other Factors*

10. Year in which the unemployment spell begun (1=1990); the reference is year 1989.
11. Year in which the unemployment spell begun (1=1991);
12. Year in which the unemployment spell begun (1=1992);
13. Studies prior to the Unemployment spell(1=Yes);
14. Training episodes prior to the unemployment spell (1=Yes);

*Number of Spells: N=2137*

**Table 2.1:** Under 25's Unemployment in % in 1995

Country	Under-25 unemployment rate <sup>(1)</sup>	Unemployed persons as a % of the population aged 15-25	Country	Under-25 unemployment rate <sup>(1)</sup>	Unemployed persons as a % of the population aged 15-25
<b>EU</b>	<b>21.5</b>	<b>9.5</b>	<b>Italy</b>	33.2	12.9
<b>Belgium</b>	24.4	8.6	<b>Luxembourg</b>	7.1	() <sup>(2)</sup>
<b>Denmark</b>	10.1	7.4	<b>Netherlands</b>	11.6	7.0
<b>Germany</b>	8.8	4.6	<b>Austria</b>	5.6	3.4
<b>Greece</b>	27.9	10.3	<b>Portugal</b>	16.6	7.1
<b>Spain</b>	42.5	17.7	<b>Finland</b>	38.2	19.8
<b>France</b>	27.3	9.7	<b>Sweden</b>	19.4	9.3
<b>Ireland</b>	19.5	8.9	<b>UK</b>	15.9	10.4

(1) Unemployment as a % of the active population (employed + unemployed)

(2) Data unreliable because of all small sample

Source: Eurostat (1997)

**Table 2.2:** Composition of Young People Unemployment by Qualifications

In %	1983	1986	1992	1996
<i>Unemployment Rate of Non-Qualified Young People</i>	25	31	28	36
<i>Share of Non-qualified Persons in the total Unemployment of the Youth</i>	54	53	52	47
<i>Unemployment Rate of Qualified Young People</i>	10.3	14.8	12.2	18.8
<i>Share of qualified young people in the total unemployment of the Youth</i>	9.7	9.6	12.5	24.5

Source: Bruno et Cazes, 1997



**Table 3.1:** Distribution of Unemployment Spells by Gender

<i>N.</i>	<i>MEN</i>			<i>WOMEN</i>		
	<b>Frequency</b>	<b>Percent</b>	<b>Cum.</b>	<b>Frequency</b>	<b>Percent</b>	<b>Cum.</b>
1	694	64.32	64.32	685	64.74	64.74
2	258	23.91	88.23	255	24.10	88.85
3	85	7.88	96.11	90	8.51	97.35
4	24	2.22	98.33	19	1.80	99.15
5	12	1.11	99.44	5	0.47	99.62
6	5	0.46	99.91	2	0.19	99.81
7	1	0.09	100.00	2	0.19	100
<i>Total</i>	1079	100%		1058	100%	

**Table 3.2:** Descriptive Statistics

<b>Variables</b>	<i>MEN</i>		<i>WOMEN</i>	
	<b>Average</b>	<b>Std.Err.</b>	<b>Average</b>	<b>Std.Err.</b>
Large Family	0.69323	0.46137	0.68620	0.46426
Entry into Unemployment <sub>1990</sub>	0.29472	0.45613	0.30151	0.45913
Entry into Unemployment <sub>1991</sub>	0.40593	0.49130	0.44045	0.49668
Entry into Unemployment <sub>1992</sub>	0.45412E-01	0.20830	0.40643E-01	0.19755
Education Level	15.310	2.1156	15.634	2.0008
Dummy var.on Education.	0.51900E-01	0.22193	0.75614E-01	0.26451
Age of the young ind. in 1992	23.797	2.8354	24.347	2.8883
Father's nationality	0.60612	0.48884	0.63516	0.48161
Technical Education	0.68860	0.46328	0.65974	0.47402
Studies prior to the unemp.spell	0.10658	0.30872	0.13705	0.34406
Training prior to the unemp.spell	0.07878	0.26951	0.13705	0.34406
Region of residence	0.09731	0.29652	0.11059	0.31377

**Table 5.1:** Results of the model without unobserved heterogeneity

Variables	MEN	WOMEN	S <sub>M</sub>	S <sub>W</sub>
Constant	-1.9011 (0.4152)	-2.2042 (0.4647)	■	
$\gamma_2$	-0.2183 (0.0919)	0.0566 (0.1005)	■	
$\gamma_3$	-0.3389 (0.1121)	-0.0340 (0.1146)	■	
$\gamma_4$	-0.5790 (0.1447)	-0.2064 (0.1369)	■	
$\gamma_5$	-0.6937 (0.1761)	-0.5315 (0.1778)	■	■
$\gamma_6$	-1.0290 (0.2300)	-0.3547 (0.1850)	■	
$\gamma_7$	-0.7219 (0.2437)	-0.0525 (0.1996)	■	
$\gamma_8$	-0.7782 (0.2847)	-0.0655 (0.2305)	■	
$\gamma_9$	-0.4748 (0.2957)	-0.3652 (0.2984)		
$\gamma_{10}$	-1.0322 (0.4526)	-0.5398 (0.3614)	■	
$\gamma_{11}$	-1.6116 (0.7089)	-0.2828 (0.3626)	■	
$\gamma_{12}$	-0.0424 (0.4169)	-0.9230 (0.5833)		
$\gamma_{13}$	-1.3693 (0.9835)	-0.3106 (0.5061)		
$\gamma_{14}$	-0.0310 (0.7055)	-0.5459 (0.7151)		
Age of the Individual <sub>1992</sub>	-0.0350 (0.0139)	-0.0183 (0.0150)	■	
Education Level	0.07291 (0.0180)	0.0737 (0.0191)	■	■
Indicator Variable on the education Level	-0.1339 (0.1943)	-0.1581 (0.1599)		
Technical kind of schooling <sub>(1=Yes)</sub>	0.0952 (0.0863)	-0.1915 (0.0862)		■
Father's Nationality <sub>(1=French)</sub>	0.2128 (0.0759)	0.1565 (0.0785)	■	■
Large Family <sub>(1=Yes)</sub>	0.0092 (0.0800)	-0.2396 (0.0822)		■
Region where living <sub>(1=Paris)</sub>	-0.1148 (0.1244)	0.2520 (0.1175)		■
Schooling prior to the unemployment spell <sub>(1=Yes)</sub>	-0.4509 (0.1202)	-0.1197 (0.1186)	■	
Training Course prior to the unemployment spell <sub>(1=Yes)</sub>	-0.0662 (0.1313)	-0.1007 (0.1074)		
Year of entry in Unemploym. <sub>1990</sub>	-0.1694 (0.0873)	-0.0523 (0.0938)	■	
Year of entry in Unemploym. <sub>1991</sub>	-0.4261 (0.0932)	-0.3149 (0.1023)	■	■
Year of entry in Unemploym. <sub>1992</sub>	-1.0722 (0.3857)	-1.6852 (0.7122)	■	■
Log-Likelihood value	-2272.0543	-2356.9427		

\*Standard Errors are in parentheses

\*\*The  $\gamma_i$  represent the baseline dummies defined as constant within each two months interval till month 26 ( $\gamma_{13}$ ) and constant thereafter ( $\gamma_{14}$  is defined respectively for Men from month 26 to month 37; for women from month 26 to month 36).\*\*\*Columns S<sub>M</sub> and S<sub>W</sub> state the significant parameter estimates, significance level 0.05.

**Table 5.2:** Results of the model with unobserved heterogeneity

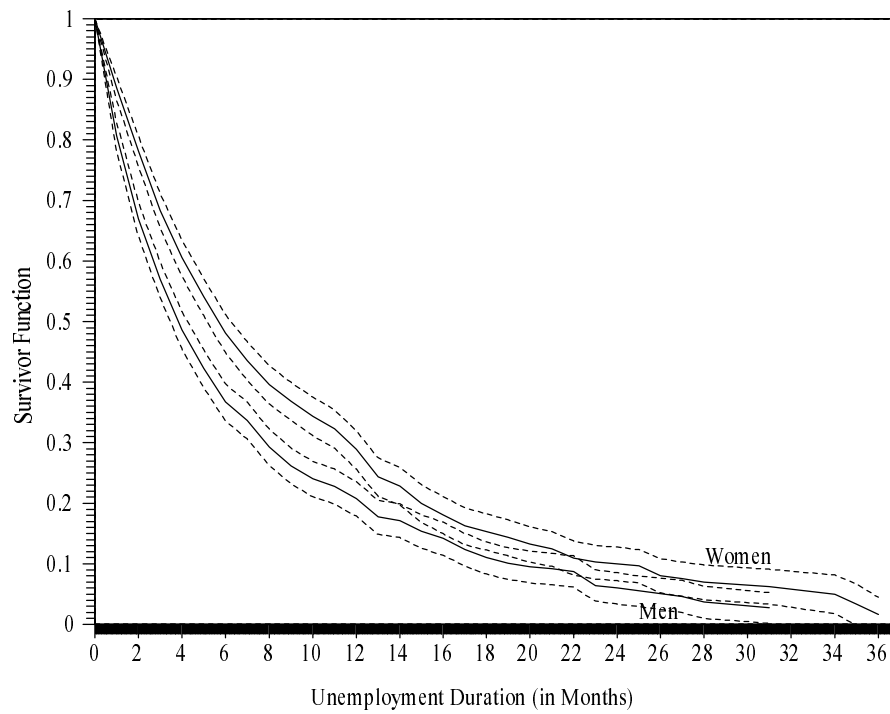
Variables	MEN	WOMEN	$D_M$	$D_W$	$S_M$	$S_W$
Constant	-1.9355 (0.4638)	-2.1776 (0.4921)				
$\gamma_2$	-0.1507 (0.1147)	0.0773 (0.1071)	☒			
$\gamma_3$	-0.2121 (0.1693)	0.01133 (0.1385)	☒			
$\gamma_4$	-0.4046 (0.2257)	-0.1399 (0.1774)	☒			
$\gamma_5$	-0.4749 (0.2791)	-0.4487 (0.2263)	☒		☒	☒
$\gamma_6$	-0.7806 (0.3372)	-0.2596 (0.2459)			☒	
$\gamma_7$	-0.4273 (0.3793)	-0.0703 (0.2871)				
$\gamma_8$	-0.4493 (0.4311)	-0.0781 (0.3336)	☒			
$\gamma_9$	-0.1049 (0.4686)	-0.2041 (0.4026)				
$\gamma_{10}$	-0.6238 (0.6047)	-0.3678 (0.4628)				
$\gamma_{11}$	-1.1818 (0.8264)	-0.0980 (0.4763)				
$\gamma_{12}$	0.4509 (0.6372)	-0.7248 (0.6707)				
$\gamma_{13}$	-0.8277 (0.9845)	-0.1010 (0.6157)				
$\gamma_{14}$	0.5515 (0.9131)	-0.3131 (0.8108)				
Age of the Individual <small>1992</small>	-0.0372 (0.0155)	-0.0198 (0.0159)			☒	
Education Level	0.0809 (0.0217)	0.0782 (0.0215)			☒	☒
Indicator Variable on the education Level	-0.1345 (0.2131)	-0.1518 (0.1686)				
Technical kind of schooling <small>(1=Yes)</small>	0.1106 (0.0968)	-0.1913 (0.0909)				☒
Father's Nationality <small>(1=French)</small>	0.2330 (0.0869)	0.1570 (0.0830)			☒	☒
Large Family <small>(1=Yes)</small>	0.0214 (0.0904)	-0.2521 (0.0894)				☒
Region where living <small>(1=Paris)</small>	-0.1058 (0.1391)	0.2754 (0.1306)				☒
Schooling prior to the unemployment spell <small>(1=Yes)</small>	-0.5087 (0.1448)	-0.1459 (0.1320)			☒	
Training Course prior to the unemployment spell <small>(1=Yes)</small>	-0.0608 (0.1479)	-0.1053 (0.1144)				
Year of entry in Unemploy. <small>1990</small>	-0.1845 (0.1000)	-0.0682 (0.1031)			☒	
Year of entry in Unemploy. <small>1991</small>	-0.4519 (0.1050)	-0.3293 (0.1096)			☒	☒
Year of entry in Unemploy. <small>1992</small>	-1.1163 (0.3969)	-1.7301 (0.7191)			☒	☒
Gamma variance	0.1819 (0.1793)	0.0932 (0.1557)				
Log-Likelihood	-2271.4004	-2356.7367				

\*Standard Errors in parentheses.

\*\* Columns  $D_M$  and  $D_W$  (where M and W stand respectively for Men and Women) state parameter estimates that are no longer significant in the model with unobserved heterogeneity.\*\*\*Columns  $S_M$  and  $S_W$  state the significant parameter estimates, significance level 0.05.

**Fig. 5.1**

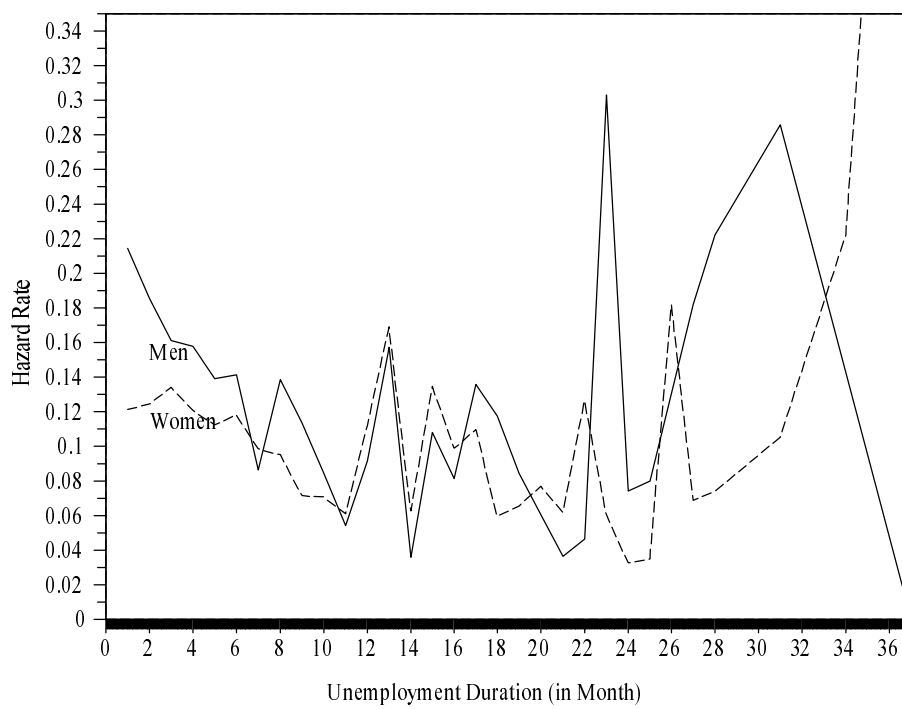
**Product Limit Survivor Functions**



\* The two survivor functions are plotted within two dashed curves that represent the significance level of the survival rates (0.05)

**Fig. 5.2**

**Estimated Hazard Function**



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