1. Introduction

The high rates of unemployment and above all their persistence in most of Western countries, are some of the reasons that justify the great number of studies, either theoretical or empirical, trying to explain its causes.

Unemployment 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.

Fitting in this framework of analysis this paper focuses on unemployment durations of french young people.

In France the increase in total unemployment since 1975 has been accompanied by a considerable rise in the number of the long-term unemployed which may be explained both by the substantial lengthening of the average unemployment duration (Moreau and Visser, 1991) mainly due to reclassification difficulties (Thélot, 1988), and by skill mismatch (Sneessens and Shadman-Mehta, 1995; Sneessens, 1995).

Youth unemployment has grown considerably too during the last twenty years and has become one of the top priorities of all french governments. Various analysis were undertaken on this topic. Some authors have used the individuals' labour market histories either to assess the effects of specific policy programs (see for apprenticeships and training programs Bonnal, Fougère and Sérandon, 1997; Werquin, 1995; for training programs Magnac, 1996a; for sanctions Abbring, van den Berg and van Ours, 1996), or for other purposes as for instance to disentangle unobserved heterogeneity from state dependence (Magnac, 1996b). A certain number of studies have focused on the impact of the minimum wages on youth unemployment (e.g. Bazen and Martin, 1991; van den Berg and Ridder, 1993; Benhayoun, 1994; Bruno and Cazes, 1997; see also Meyer and Wise, 1983; Dolado et *al.,* 1996). Others have analyzed the unemployment durations of the young people to answer to some specific questions as for instance Moreau and Visser (1991) and van den Berg and van Ours (1996). The former authors have concentrated their work on the computation of reservation wages and duration elasticities. van den Berg and van Ours (1996) have examined to what extent the individual exit probability out of unemployment for young job seekers displays duration dependence and the relative importance of this and unobserved heterogeneity.

The target of this paper is to provide a microeconometric study of the determinants of unemployment durations of French young people while answering to different questions. The first of them regards the presence of duration dependence and its sign (a negative duration dependence implies that the hazard rate decreases as the unemployment duration lengthens). Since policy programs may be differentiated according to the kind of duration dependence, the knowledge of this element seems to be crucial. Secondly it studies the influence of some observed factors on the youth's probability to exit unemployment, to evaluate to what extent they are at the origin of different conditions to access the labour market. Finally it takes into account unobserved heterogeneity.

The available dataset comes from the wave 1990-1992 of the Enquête Emploi (i.e. the French Labour Survey) and the "Module Jeunes" collected by the *Institut National de la Statistique et des Etudes Economiques* (INSEE). It contains information about the trajectories of 5824 young individuals on the labour market. Those having experienced at least one unemployment spell have been selected for the analysis of unemployment durations; this turns out in a sample of 2048 unemployment spells.

The empirical analysis uses semi-parametric and parametric hazard models with grouped duration data.

In many data sets observations on unemployment durations are grouped meaning that only time intervals are known for the starting date of the spells. This is the case for the French Labour survey where the interviewed individual has for instance to declare which was his occupation in the months preceding the interviews. Methods for analyzing grouped duration data (see Prentice and Gloecker, 1978) are then likely to be more correct.

Following the semi-parametric modelling strategy a piecewise constant baseline hazard is specified and estimated along the lines used by Prentice and Gloecker (1978). According to the parametric modelling both an exponential and a Weibull specifications have been adopted. To capture individual unobserved heterogeneity a gamma mixing distribution has been used as suggested in Meyer (1990), 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; some descriptive statistics are given. The models used in the analysis and methods of estimation are presented in section 4. Section 5 will be devoted to the description of the tests used for model choice. In Section 6 the main findings will be discussed. Some conclusions are drawn in Section 7.

2. The French Labour Market for the Youth

The problem of youth unemployment has been one of the top policy issues of all French governments during the last twenty years, being not desirable both from an economic and social point of view. In most cases the young unemployed have had no experience on the labour market and their exclusion from this is likely to reduce the human capital they acquired during their studies.

Since 1983 the unemployment rate of french young people (i.e. people aged between 15 and 25) has seldom been below 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 problem. 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) as illustrated by the following table

[*Table* 2.1][1]

Persistence in France of such a high youth unemployment rate is really astonishing and this for various reasons.

First their rate of schooling did not stop increasing these last years. The share of non active 18-years old in education, attained in France in 1995 84% of the youth population (Eurostat, 1997). The number of people having no qualification passed from 49.8% of the active population in 1962 to 21% in 1990, while both the number of those having a "baccalauréat" (that is the qualification corresponding to the examination allowing university entrance) and the share of those having a level of education higher than the "baccalauréat", raised : the former from 5.8% in 1962 to 13.1% in 1990, the latter from 2.7% in 1962 to 15.2% in 1990 (Bruno and Cazes, 1997).

[1]Tables and the graphs are reported in Appendix 1.

Secondly during the same period many and diversified policies and supplementary programs were conceived to make easier the integration of the youth in the labour market [2].

Finally demographic reasons did not contribute to increase unemployment of the young people, indeed the total population of the youth relative to the overall population has 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 leaving the schooling system, the direct access to employment being increasingly rare. Furthermore young people face the difficulty of finding a stable job; they often experience fixed term contracts intersected with unemployment spells. This is illustrated by the fact that average unemployment durations are lower for the youth than for the adults whereas cumulated durations are higher for the former (Bruno and Cazes, 1997).

Moreover the employed young people face a greater risk to enter unemployment than the adults as shown in table 2.2. During a recession period, firms sacrifice firstly young individuals' jobs to preserve those of the adults (Bruno and Cazes, 1997)

[*Table* 2.2]

It must also be noticed that even if the higher share in youth unemployment is represented by non-qualified persons, the number of qualified individuals (where by "qualified people" it is meant those having at least a *baccalauréat)* entering unemployment does not cease growing as illustrated in the following table 2.3 implying that they also encounter many difficulties 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 hand to the inadequacy between the training and schooling system and the real needs of the economy (Sneessens, 1994).

[*Table* 2.3]

3. The sample and the variables

3.1. The data base

Available data for the analysis are extracted from both the 1990-92 wave of the French Labour Force Survey ("Enquête Emploi") and a special survey led in 1992, called "Module Jeunes", that reports some additional information about young people. Both surveys have been carried out by the *Institut National de la Statistique et des Etudes Economiques* (INSEE).

Data come from a retrospective survey, the data source is thus 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 rebuilding long histories, but has also a major disadvantage: the lack of memory of the interviewed individuals may generate errors in the observations and by there prohibit very precise observations (see Fougère, Florens, Kamionka and Mouchart, 1995; Magnac and Visser 1996).

[2] For a synthesis of policies and their history see Bonnal, Fougère and Serandon (1997); Lechene and Magnac (1995).

Interviews were carried out on three dates: January 90, March 91 and March 92. In the survey 4237 households are present at all the dates and at least an individual aged between 18 and 29 in 1992 belongs to them. These young persons are asked to give more details about their occupational history and on family and individual status since they were 16.

The French Labour Force Survey records the situation of the individual at the date of the survey. It reports also his/her main occupation[3], on a monthly basis, during the previous year while the "Module Jeunes" reports this information since the young people were 16 till December 1988. Individuals' trajectories are then rebuilt over the period going from January 1989 to March 1992 (for a comment on the coherence degree between information in the "Module Jeunes" and the "Enquête Emploi" see Magnac, 1995).

The selection of the sample operated at the same time by families and by individuals can introduce some biases (Magnac, 1995). On the one hand the French Labour Survey is a survey by households then the young individuals living mostly out of them are not interviewed in the survey. In addition, given that the selected families are those present at the three dates, it would be necessary to evaluate if the disappearance of some of them from the survey (either caused by the refusal to answer or by mobility) affects the results (Magnac, 1995).

Data are multistate and multispells. By multistate, one understands data which provide information on the whole trajectory of the individuals on the labour market during the observation period. The labour market can be thus represented by a set of states through which individuals can pass. 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 multispells 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.

The available dataset contains information about the trajectories of 5824 individuals on the labour market. To form the sample used in the analysis the individuals who have experienced at least one unemployment spell have been selected. It is assumed that one spell ends when an event occurs i.e. when a person leaves a particular state (e.g. an unemployed individual can find a stable employment, follow a training course, etc.) otherwise the spell is right censored. Left-censored spells (i.e. either spells that were in hand in January 1989 - that is the beginning of the survey - or those whose starting date is not known owing to the presence of attrition) have been discarded from the sample.

This selection turns out in a sample of 2048 unemployment spells, 1038 of which experienced by young men and 1010 by young women (the number of individuals being respectively 680 men and 661 women). Unemployment spells, rather than individuals, have been taken as unit of analysis. This amounts to make the implicit assumption that multiple durations of the same individual are independent from each other (see Amemiya, 1985).

[3]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.

3.2. Preliminary description of the sample

Various characteristics concerning the young people are available in the data base and have been used as explanatory variables to study in which manner they influence the hazard rate. They are: the age of the individual, his/her level of education, the french nationality of the father of the young person, the year of entry in the unemployment spell, the fact of having attended a technical school, of belonging to a large family, of living in Paris, and finally of entering unemployment right after either having left the schooling system or having followed a training program.

To summarize the variables used in the empirical analysis some descriptive statistics are reported in the following table 3.1.

[*Table* 3.1]

A few comments are in order to explain their meaning.

The age of the individual is not a time-varying variable, indeed it is the age in 1992, thus people belonging to the sample studied are aged between 18 and 29 in 1992. Unemployed women are, on average, older than men.

The young person's education level is expressed in terms of "theoretical age of end of studies". Each value of this variable corresponds then to the level of qualification attained by the individual when he/she left the schooling system. For instance, a value equal to 18 states that the young person left it with a "baccalauréat"; it does not mean that he/she left when being 18 years old.

The average value of this variable (see table 3.1) states that young unemployed have a low qualification level. Only 78 men (over 680) and 69 women (over 661) have an education level higher than the "baccalauréat", and in both cases their father is french-nationality. A closer analysis revealed that the lowest values correspond mostly to individuals whose father is 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.

Dealing with the level of education a problem of missing values had to be solved. A specific procedure[4] was applied to replace the missing information. It consisted in regressing the education level (without the missing values) on some explanatory variables (i.e. the age of the person, the region where living, the fact of belonging to a large family, and the nationality of the father) and using afterwards their coefficient estimates to rebuild the missing information. To control for the quality of the adjustment a dummy variable has been introduced in the modelling (D'Addio, 1997, 1998).

As shown in table 3.1 a great number of young unemployed attended a technical school; their average qualification level corresponds to the BEP that is a technical certificate obtained after 11 years of schooling.

Referring to the nationality of the father of the young person, its average value suggests that many young unemployed persons have a father's of non-french nationality. Different reasons may explain this. First it must be noticed that this variable reports information only about the nationality of people born in the metropolitan France. Secondly the study of unemployment often implies to focus on the weaker part of the population that is the one that has greater difficulties to enter the labour market. Indeed nationality may act as a signal of the cultural and social environment in which the individual lives.

[4]Suggested by B. Cockx.

The variable that states whether the young person belongs to a large family has been built using the number of his/her brothers and sisters reported in the survey. With the term large family it is thus meant a family where the number of children is equal or greater than three. The average number of children is equal to 2.7 when the father is french-nationality and to 3.7 when he is not french-nationality. Most of the unemployed people seem then to belong to a large family. It will be interesting to consider the effects related to income resources, the lack of data on income and benefit does not allow to do this.

Only few people in the sample live in Paris, most of them live in other french towns.

The other variables presented in table 3.1, i.e. the year in which the unemployment spell started and the status of the youth prior to it, have been used because they allow both to take further observable differences into accounts, and to control for unobserved heterogeneity.

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

[*Fig.* 3.1]

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 χ^2 distributed with $k-1$ degrees of freedom, k being the number of subgroups. The log-rank statistic with the value of 23.93 (p-value 0.9999) and one degree of freedom stresses the differences between the two groups.

The computation of average unemployment duration neglects the fact that a part of the unemployment spells (and precisely those that are still in hand at the end of the survey) is right-censored so that their real duration is unknown. For this reason the use of the median duration computed by the Kaplan-Meier estimator has to be preferred: this is equal to 3.84 months for men and to 5.68 months for women.

4. The models

4.1. Introduction

The empirical analysis in this paper is developed in the framework of econometric duration models. A central concept in theories of unemployment duration is the exit or hazard rate i.e. the instantaneous probability of leaving a particular state (here unemployment) at time t conditional to not having left till the moment immediately before[5].The hazard function is closely related to other concepts useful to describe the probability distribution, as for instance the survivor function representing the probability of "surviving" in a specific state.

In job search theory the hazard rate is equal to the product of the probability of receiving a job offer on a given period and the probability that such an offer will be accepted by the unemployed. The probability to accept depends on the individual reservation wage.

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

Various factors may influence the hazard rate during the unemployment spell and cause it to change, implying duration dependence. Discouragement effects may appear, individual's abilities may decline or deteriorate as unemployment spell lengthens. Even if they are not evident, these effects may be perceived by the employers who may use long term unemployment as a proxy for workers' productivity. In any case all these mechanisms may lead to a decreasing hazard rate over the unemployment spell. On the other hand reservation wages may decline owing for instance to decreasing unemployment benefits as unemployment goes on.

The great majority of datasets does not contain variables that can be interpreted as reservation wages. Nevertheless it is possible to impose the structure of search theory when disposing of information about the accepted wages of persons who find a job or the individual unemployment income.

Since all these variables are absent in the available dataset, a reduced form model will be used instead of a structural one. This is based on the specification and estimation of the hazard function where the probability of leaving unemployment is linked directly to the regressors and to the elapsed unemployment duration without making use of the search theory modelling framework. Flexible specifications are to be preferred, indeed they allow the hazard rate to vary with duration without being too tightly constrained.

Various regressors have been introduced but firstly unemployment durations of men and women have been compared using a non-parametric estimator: the Kaplan-Meier (1958) survival rate (see *supra* Fig. 3.1). These estimates may help to have a preliminary idea on the duration distributions of the two groups, by the way 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.

Different proportional hazard models have been specified and they have been estimated separately for men and women, the target being to assess the impact of individual, socio-demographic factors on their probability of leaving unemployment and to study how the hazard rate changes with the elapsed duration for each group.

4.2. Specification of the hazard without unobserved heterogeneity

The models used to represent the conditional probability of leaving unemployment are of the proportional hazard form (Cox, 1972). More precisely they are grouped duration data (or discrete-time) hazard models.

The continuous proportional hazard function writes

$$\lambda(t|x_i) = \lambda_0(t)\exp(x_i'\beta) \tag{4.1}$$

The hazard function is thus related to a set of explanatory variables x_i, here time-invariant, and to the "baseline" hazard rate $\lambda_0(t)$. The main feature of this model is that the baseline hazard is not constrained to belong to a specific parametric family. The usefulness of such a model has been investigated in different works among which it is necessary to remember Prentice and Gloecker (1978), Moffitt (1985), Han and Hausman (1990), Meyer (1990, 1995). Familiar exponential and Weibull regression models are special cases of (4.1).

In equation (4.1) 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, adequate data are usually not accessible. Especially microeconometric data, like panels, are often collected on a weekly, monthly or even yearly basis, and as a result only time intervals during which events have occurred can be specified. This is the case with the French Labour Survey. The use of grouped duration data hazard models is then likely to be more appropriate.

Let us suppose that the underlying continuous durations are only observed in j disjoint time intervals $[0 = a_0, a_1), [a_1, a_2), [a_2, a_3), ..., [a_{J-1}, a_J = \infty)$ with the $j-th$ interval defined as $[a_{j-1}, a_j]$. The probability of exit in the j interval for person i is

$$Pr\{T \in [a_{j-1}, a_j)|x_i\} = S(a_{j-1}|x_i) - S(a_j|x_i) \tag{4.2}$$

where the survivor function at the start of the jth interval is

$$Pr\{T \geq a_{j-1}|x_i\} = S(a_{j-1}|x_i) \tag{4.3}$$

The hazard in the jth interval is thus given by

$$Pr\{T \in [a_{j-1}, a_j)|T \geq a_{j-1}, x_i\} = 1 - \frac{S(a_j|x_i)}{S(a_{j-1}|x_i)} = h_j(x_i), \text{ say} \tag{4.4}$$

Following Meyer (1990,1995) (4.4) can be written as

$$h_j(x_i) = 1 - \exp[-\exp(x_i^{'}\beta + \gamma_j)] \tag{4.5}$$

where

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

Note that this follows from the proportional hazard specification without any other distributional assumption.

The γ_j $(j = 1, .., k)$ in (4.5) can be treated as parameters to be estimated along with β (Prentice and Gloecker, 1978; Meyer, 1995; Stewart, 1996).

To simplify suppose that the duration for each person i corresponds to the interval of unit length $[t_i - 1, t_i)$ (Jenkins, 1997) then the sample log-likelihood expressed in terms of the hazard function is

$$\begin{aligned} \log L &= \sum_{i=1}^{n} \left\{ \{c_i \log \left[h_{it_i}(x_i) \prod_{j=1}^{t_i - 1} (1 - h_{ij}(x_i)) \right] \right. \\ &\quad \left. + (1 - c_i) \log \left[\prod_{j=1}^{t_i} (1 - h_{ij}(x_i)) \right] \right\} \end{aligned} \tag{4.6}$$

that can be rewritten as (Allison, 1982)

$$LogL = \sum_{i=1}^{n} c_i \frac{h_i(x_i)}{1 - h_i(x_i)} + \sum_{i=1}^{n} \sum_{j=1}^{t_i} \log\left(1 - h_{ij}(x_i)\right) \tag{4.7}$$

where c_i is the censoring indicator taking the value 1 if the spell is completed and 0 if it is right-censored.

Since an individual can only occupy a state or leave it, grouped duration data hazard models have an appealing relationship to binomial models as already noticed in Allison (1982), Kiefer (1988b, 1990) and Jenkins (1995). Each individual or each spell may be seen as contributing n_i observations, one for each interval entered. This amounts to form a sample of size $N = \sum_i n_i$ observations (see Hujer, Maurer and Wellner, 1996,1997). Then a new indicator variable is defined

$$y_{it} = 1|_{\ [t-1,t]}\ (T_i) \tag{4.8}$$

$y_{it} = 1$ if individual i leaves in the tth interval and $y_{it} = 0$ otherwise (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:

$$\log L = \sum_{i=1}^{n} \sum_{j=1}^{t_i} \{ y_{ij} \log h_{ij}(x_i) + (1 - y_{ij}) \log[1 - h_{ij}(x_i)] \} \tag{4.9}$$

that is the log-likelihood for the regression of dichotomous dependent variables. In particular the log-likelihood is the same as the one for a generalized linear model of the binomial family with complementary log-log link (Allison, 1982; Jenkins, 1995). Indeed the above equation (4.5) may be solved to yield the so-called complementary log-log function:

$$\log\left[-\log(1 - h_j(x_i))\right] = \gamma_j + x_i'\beta \tag{4.10}$$

The specification in (4.5) allows for a very flexible baseline hazard. Thus it is possible to specify a distinct parameter either for each duration interval or for a longer duration interval. In both cases γ_j can be interpreted (Jenkins, 1997) as the logarithm of the integral of the baseline hazard over the relevant interval. Alternatively on can use a parametric function to represent the sequence of the γ_j.

Both approaches have been applied in this study.

According to the former, the baseline hazard, γ_j has been defined as constant within two months intervals up to the 26th month and constant thereafter. The first interval is absorbed in the constant; the last interval groups durations from month 27 to month 37 and 36 respectively for men and women. This specification of the baseline hazard is very useful. On the one hand it allows a high degree of flexibility as to duration dependence without imposing strong restrictions on the form of the baseline hazard (indeed even if constant in each duration interval, it can vary across different duration intervals); on the other hand it can be used to test other parametric forms (see Meyer, 1995) as it will be shown in Section 5. Moreover one of the main advantages of this model is that it provides a 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.

Two functions have been used to model a parametric baseline hazard: the exponential and the Weibull. In the exponential regression model $\lambda_0(t) = \lambda$, then $\gamma_j = \ln\lambda - \ln(t_j - t_{j-1})$. In the Weibull model $\lambda_0(t) = \lambda\sigma t^{\sigma-1}$ where σ is the shape parameter and $\gamma_j = \ln\lambda + \ln(t_j^\sigma - t_{j-1}^\sigma)$ (see Kiefer, 1990; Narendranathan and Stewart, 1990).

4.3. Specification of the hazard with unobserved heterogeneity

In the models presented above it is assumed that all the differences existing among individuals can be explained by the set of covariates, i.e. by the set of observed characteristics. In reality, it is not possible to observe all the factors suitable to differentiate individuals.

As it has been noticed in various studies (e.g. Lancaster, 1979) the lack of control for unobserved heterogeneity may lead to spurious duration dependence (Elbers and Ridder, 1982) and to bias in the parameter estimates of the hazard function (Lancaster, 1990; 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)

$$\lambda_i(t|x_i,\varepsilon) = \lambda_0(t)\varepsilon_i \exp[x_i'\beta] = \lambda_0(t)\exp[x_i'\beta + \log(\varepsilon_i)] \tag{4.11}$$

where ε_i is a positive-valued random variable with density $\mathrm{f}_\varepsilon(\varepsilon)$. If ε is assumed to have finite mean, one can normalize $E(\varepsilon) = 1$. (Stewart, 1996)

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). A density for ε is indeed required to enable the calculation of the log-likelihood.

The most commonly used parametric mixing distribution since Lancaster (1979) has been the Gamma distribution, primarily for mathematical convenience. This distribution has been introduced in this study to model unobserved heterogeneity both in the semi-parametric and parametric hazard functions (details on the parametrization of the gamma function are given in Appendix 2).

Following Meyer, (1990, 1995), Stewart (1996), Jenkins (1997), the survivor function can be written as

$$\begin{aligned} S(t_i|x_i) &= \int_0^\infty exp\left[-\varepsilon_i \sum_{j=1}^{t_i} exp\left(x_i'\beta + \gamma_j\right)\right] d\Gamma(\varepsilon_i) \\ &= \left[1 + \sigma^2 \sum_{j=1}^{t_i} \exp\left(x_i'\beta + \gamma_j\right)\right]^{-\frac{1}{\sigma^2}} \end{aligned} \tag{4.12}$$

where σ^2 is the variance of the gamma-distributed random variable.

The log-likelihood writes (Jenkins, 1997)

$$\log L = \sum_{i=1}^{n} \log\left\{(1-c_i)\,A_i + c_i B_i\right\} \tag{4.13}$$

with

$$A_i = \left[1 + \sigma^2 \sum_{j=1}^{t_i} \exp\left(x_i'\beta + \gamma_j\right)\right]^{-\frac{1}{\sigma^2}}$$

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

where c_i is the censoring indicator, γ_j is a function describing duration dependence in the hazard rate and σ^2 is the variance of the gamma-distributed random variable.

5. Testing for model choice

The parameter estimates obtained from the estimation of a piecewise constant baseline hazard $\pi_S = (\gamma, \beta)$ can be used to test assumptions about the shape of the baseline hazard (Meyer, 1995). To this end two different tests have been implemented: the Hausman (1978) test and the likelihood ratio test.

1. *The Hausman (1978) test*:
   Semi-parametric estimates (π_S) are compared to those obtained with the baseline hazard restricted to a specific functional form (π_P) (Meyer, 1995). Under the null hypothesis that the functional form is correct, both estimators are consistent. Under the alternative only the semi-parametric estimators are consistent and the two sets of estimates will diverge. This test thus makes possible to evaluate whether the differences which exist between the two sets of estimates are significant.[6]
   Let's π_S and π_P denote the parameters defined *supra*. Then

   $$(\widehat{\pi}_S - \widehat{\pi}_P)'(Var(\widehat{\pi}_S) - Var(\widehat{\pi}_P))^{-1}(\widehat{\pi}_S - \widehat{\pi}_P) \underset{a}{\sim} {\chi^2}_{p+T} \tag{5.1}$$

   under the null assumption, where p is the dimension of β.
   The test can be performed by using a subset of parameters rather than $\pi = (\gamma, \beta)$. β is indeed easier to use than the complete vector π, because both $\widehat{\beta}$ and the asymptotic variance $Var(\widehat{\beta})$ are calculated directly by the maximization routines (Meyer, 1995).

2. *The likelihood ratio test:*
   Under the null hypothesis that the additionally included variables do not significantly improve the model fit, the likelihood ratio test statistic follows a χ^2 with p degrees of freedom, where p is the number of additionally included variables (Blossfeld and Rohwer, 1995). It is computed as two times the difference of the log-likelihoods of the models to be compared.
   In this study it has been used to compare parametric and semi-parametric hazard specifications.

6. Main findings

6.1. Some Preliminary Indications

The Kaplan-Meier estimator (see *supra*) used to compare the unemployment durations of men and women is non-parametric, by there it does not allow to take account for either observable or unobservable heterogeneity. To study the effects that observed factors can exert on the rate of hazard, a multivariate analysis has been then applied using proportional hazard models. They allow 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).

[6]For a commentary on the power of the test see Arellano and Bond (1991).

A short remark on the interpretation of the regressors is in order.

Two continuous regressors are introduced; they are the age and the education level. The majority of the regressors is however of the categorical type. Dummy variables are thus used to code the presence or non presence of a specific feature. The parameter β_j measures then the respective distance between the j category and the reference category.

Maximum likelihood estimates of both semi-parametric and parametric specifications of the hazard are given in of tables 6.1a and 6.1b (where (a) stands for men and (b) for women).

[*Table* 6.1a]
[*Table* 6.1b]

The corresponding estimates of the models with unobserved heterogeneity are given in tables 6.2a and 6.2b.

[*Table* 6.2a]
[*Table* 6.2b]

6.2. Individual Characteristics

The age of the individual, his(her) level of education and finally whether he/she has followed a technical kind of schooling are the variables incorporated in the analysis to describe the personal characteristics of the young persons.

The age could 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 person may have more difficulties to reclassify himself/herself on the labour market. Within the search theoretical framework several explanations for negative age effects can be offered: for instance employers may regard higher age as a sign of lower productivity. Moreover older persons are less mobile geographically and professionally.

As reported in tables 6.1(a,b) and 6.2(a,b) the negative sign of the age coefficient, and the fact that it is significant (at least relative to men unemployment spells) show that the older the individual, the weaker his 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. The negative effect seems then to prevail on the positive one, where the age accounts for the individual's experience. This kind of effect seems rather robust, indeed it appears in various studies in a more or less significant way (Lancaster, 1979; Nickell, 1979; Cases and Lollivier, 1994; Bonnal and Fougère, 1990; Florens and *al.*, 1990; Magnac, 1996a).

Referring to the level of education, one should expect that the higher, the higher the probability of leaving unemployment since more educated people have a greater human capital and are expected to have a higher arrival rate. Indeed, it is reasonable to think that the higher the level of education, the higher the expected future wage; thus the relation between the hazard rate and the education level should be positive.

The sign of the estimated coefficient, and the fact that is significant confirms the described relation. This is verified, at the same time, for men and women.

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

By observing tables 6.1(a,b) and 6.2(a,b) one sees that it has a significant impact only on the hazard rate of young women, and that this effect is negative. It seems then that for employers technical education is a low-quality indicator of young women productivity. For men on the contrary the effect, even if not significant, is positive. The same conclusion has been reached in the study of Moreau and Visser (1991); these authors found that men having a technical education leave unemployment more easily.

6.3. Socio-demographic characteristics

Family situation is likely to affect the job-search efforts of young unemployed, then it must be studied with care. 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 hazard rate justifies the introduction of such an information in the present study; indeed the fact of living in a more or less active environment may be a decisive factor for leaving unemployment.

Most of the studies on the determinants of the hazard rate take the nationality of the unemployed individuals into account. Its effect on the probability of leaving unemployment cannot be determined with certainty *a priori.* However one could expect that migrants encounter some difficulties to enter the labour market of another country.

In this study a variable that represents the nationality of the father of the unemployed person has been introduced, the nationality of young individuals not being reported in the available data base. Its impact on the hazard rate may be very difficult to evaluate. Young individuals whose father is not french-nationality may be either french-nationality either non french-nationality. In the former case one could wonder why they should encounter more difficulties to enter the labour market than those whose father is french-nationality. Different factors might contribute to this issue, for instance the country of origin of the father that is reflected in most cases in the young person's last name (and may act as a signal of his nationality) as well as the family and social environment.

By observing tables 6.1(a,b) and 6.2(a,b) it can be noticed that individuals whose father is French nationality have a higher probability of leaving unemployment. This is verified at the same time for young men and women, even if in a more significant way for the former population. In much of the existing works on reduced form models or in other modelling frameworks on unemployment durations nationality variables yield similar sign patterns (Lynch, 1985; Magnac, 1996a).

After correcting for different heterogeneity sources migrant workers still have a disadvantage on the labour market even if this is significant only referring to men.

The structure of the family could play an important role on the hazard rate; this role can however be different according to various factors as for instance the age and the sex of the unemployed individual and the income resources of the family.

Tables 6.1(b) and 6.2(b) show that there is a negative relation between the hazard rate of women and the dimension 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 a variable introduced in the modelling states whether the young person lives either in Paris or in other communes with a smaller number of inhabitants. As reported in tables 6.1(a,b) and 6.2(a,b) the fact of living in Paris has a positive and significant effect only on the hazard rate of the young women contributing then to rise their chances to leave unemployment. For men the effect is negative even if not significant. It can be interpreted using sociological economics and in particular the so called work-norm that states that a man should work to receive an income. It is then possible that in smaller communities the traditional work-norm is strongly felt than in larger communities.

These results show that human, cultural and geographic environment are important factors 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 unemployed people. 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.

6.4. Other factors

Some other variables have been introduced in order to take into account further observed differences among young individuals. They are both variables which state the year in which the unemployment spell started (and may thus capture effects related to the country's economic situation), and variables that describe the status of the individuals prior to the unemployment spell, specifically if the individuals entered it right after either having left the schooling system or having had a training spell.

As shown in tables 6.1(a,b) and 6.2(a,b) the year during which the unemployment spell began is very important, having a strong impact on the hazard rate. This thus seems very sensitive to the economic situation and in particular to the recession starting in 1991 in France.

Various arguments can be used to explain the evolution of the hazard rate according to the date of entry in the unemployment spell. On the one hand, the number of entries into unemployment, which often depends on seasonal effects (Abbring and *al.* 1994), can affect the intensity of the competition for the available vacancies among the new entrants, and by there influence the hazard rate. On the other hand, the average quality of the new cohorts of unemployed may vary during the year and the seasons and therefore affect the probability of leaving unemployment.

The two variables stating the occupation of the young person prior to the unemployment spell, may be seen as useful instruments to control and to correct for unobserved heterogeneity; people having experienced a training spell or having left the schooling system right before entering unemployment are likely to be characterized by particular features that have not been taken into account in the analysis because not observable, but nevertheless necessary to differentiate individuals.

To enter unemployment after the end of the studies seems to rise unemployment durations. This may be due to various reasons. For instance it is reasonable to think that people leaving the schooling system with the best results have more chances to find a job (quality of the entrants). Still, the job search process is likely to require some time, effort, and also experience; all these factors can contribute to make slower the exit out of unemployment for the new entrants.

Finally, having followed a paid training course prior to unemployment has a negative impact on the probability of leaving it, even if it is not significant. This effect could be interpreted either in terms of the quality of the new entrants either as a measure of the efficiency of training programs.

6.5. Comparison of the estimated models

First of all it must be noticed that the effects of the explanatory variables in the semi-parametric model are very similar to those obtained with the Weibull and exponential specifications (see tables 6.1(a,b) and 6.2(a,b)).

Turning to the semi-parametric baseline hazard estimates, one can observe that there is evidence of a negative duration dependence for both sexes, even if the baseline dummies are significant only for men. However it must be noticed that they are no longer significant after the introduction of the unobserved heterogeneity correction even if they maintain in most cases their negative sign.

During the first eleven (for men) and nine (for women) months the hazard decreases and then it starts rising; a period of considerable negative duration dependence is followed by a period of positive duration dependence. After the first year of unemployment the probability of leaving unemployment rises as the spell lengthens.

For men the hazard rate after the first year is usually below its initial value, with one peak corresponding to the last months of the second year. For women the observed tendency is the same even if weaker. Also negative duration dependence seems to be smaller for women than for men.

The parameter estimates of the model with a piecewise constant baseline hazard have been compared to the parametric ones using two different tests: the Hausman (1978) and the likelihood ratio test whose values are reported in tables 6.3 and 6.4.

[*Table* 6.3]
[*Table* 6.4]

Using the former test to compare the piecewise constant hazard model and the exponential when unobserved heterogeneity is not modelled, it results that the null hypothesis cannot be rejected for women only. Indeed for men the test states that only the semi-parametric estimator is consistent. When comparing the estimates of the piecewise constant hazard model with those of the Weibull we get that for both sexes the null hypothesis (under which both estimators are consistent) is not rejected. When unobserved heterogeneity correction is incorporated the null hypothesis cannot be rejected for both comparisons and groups implying that the differences between the estimators are not significant.

To analyze the model fit a likelihood ratio test statistic has been performed.

When unobserved heterogeneity is not taken into account the null hypothesis of an exponential hazard is again rejected for men, while it is not for women. For both sexes the null hypothesis of a constant hazard cannot be rejected when the unobserved heterogeneity correction is present.

From the comparison between the Weibull and the piecewise constant hazard model it results that for both sexes and either when the correction for unobserved heterogeneity is not introduced or when it is the use of the less constrained model (i.e. the piecewise constant) does not seem to ameliorate the fit.

Turning to the evaluation of the manner in which the hazard rate changes with the elapsed duration, one can see that σ , i.e. the duration dependence parameter of the Weibull model, is negative (implying negative duration dependence as in the semi-parametric specification) and significant for both sexes. When the unobserved heterogeneity correction is incorporated duration dependence parameter σ is no longer significant then the null hypothesis of a constant hazard cannot be rejected.

For both sexes according to the tests performed the specifications that seem the most adequate to represent probability of leaving unemployment are the Weibull when unobserved heterogeneity is not modelled and the exponential when it is.

$[Table\ 6.5]$

The conclusions reached are consistent with the theoretical requirements that negative duration dependence is moderated by the correction of unobserved heterogeneity.

This result is very important primarily from a policy point of view. Negative duration dependence often implies the existence of discouragement effects; policy programs could then focus on preventing people become long-term unemployed (van den Berg and 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; these individuals may be then orientated towards specific training activities. When true negative duration dependence is absent, as it seems to be the case here, efforts could be concentrated on the individuals with the most unfavorable characteristics by means of non-temporary targeted policies like specific training programs or permanent subsidies on low wages.

The resulting hazard functions are plotted in Fig. 6.2 and Fig. 6.3 for men and women respectively. In constructing the graphs all the regressors have been put at their sample averages. The figures hence represent hazard time paths for average men and women.

$[Fig.\ 6.1]$
$[Fig.\ 6.2]$

As shown in the following graph the probability of leaving unemployment is almost always lower for women than for men.

$[Fig.\ 6.3]$

The hazard functions corresponding to the specification with unobserved heterogeneity are plotted in the following graphs.

$[Fig.\ 6.4]$
$[Fig.\ 6.5]$

The estimation of the semi-parametric baseline hazard gives a non-significant unobserved heterogeneity parameter, and this both for men and women. This may also be due to the flexibility of the baseline hazard that in this latter case can partially capture it.

This result differs from the one obtained by van den Berg and van Ours (1996) on a similar population. In their study 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 being non available. Secondly data used in their article are administrative (they come from the ANPE - *Agence Nationale Pour l'Emploi*) and differ in many respect from those of the INSEE.

The unobserved heterogeneity parameter is on the contrary important and significant in the exponential specification of the baseline hazard that is the one retained when the gamma correction is introduced.

Nevertheless it is necessary to say that one must be careful about drawing conclusions about duration dependence when using parametric models like the Weibull and the exponential that strongly constrain the shape of the baseline hazard which in reality may vary non-monotonically with duration. Indeed, conclusions about the importance of unobserved heterogeneity are likely to be more reliable when a flexible specification for the baseline hazard is used (see Dolton and van der Klaauw, 1995).

However the results obtained stress the necessity to control for unobserved heterogeneity, indeed its failure may lead to formulate false conclusions on the shape of the hazard function.

7. Conclusion

This paper aimed both at the analysis of the factors that can affect the probability of leaving unemployment of french young people and at the evaluation of duration dependence while controlling for unobserved heterogeneity.

In order to assess the differential effects between men and women, estimations have been performed separately on the two subgroups.

Various characteristics (see section 3) have been introduced in the analysis developed in the framework of econometric duration model. A semi-parametric and two parametric hazard functions have been specified using grouped duration data (see Prentice and Gloecker, 1978). To capture individual unobserved heterogeneity a gamma mixing distribution has been used.

Concerning model specification, some tests (see Section 5) have been used to compare semi-parametric and parametric baseline hazard estimates. According to these the best specifications to represent the probability of leaving unemployment for both sexes are respectively the Weibull (with a negative dependence parameter) when unobserved heterogeneity is not modelled and the exponential when it is.

For both groups the hazard function, before heterogeneity correction, show negative duration dependence. It is then important to remark that when unobserved heterogeneity is modelled, there is no longer evidence of negative duration dependence. The gamma correction for unobserved heterogeneity moderates the effects of duration dependence and this is consistent with the theoretical framework. Moreover unobserved heterogeneity parameter is significant in the parametric specification of the hazard rate retained to represent the probability of leaving unemployment (i.e. the exponential).

This result implies firstly that discouragement effects are not likely to be present, secondly (given that unobserved heterogeneity seems to be important) that from a policy point of view it could be useful to screen people flowing into unemployment and to identify those having the most unfavorable characteristics. Efforts could be concentrated subsequently on those individuals by means of non-temporary targeted policies like specific training programs or permanent subsidies on low wages.

Some of the characteristics introduced, affect in the same way the probability of leaving unemployment of the two populations studied. Both a higher education level and the fact of having a father of french nationality seem to reduce average youth unemployment durations. It is worthwhile to notice that the year in which the unemployment spell began has a strong impact on the hazard rate that seems to be very sensitive to the economic situation and moreover to the recession started in France in 1991.

Some factors having a significant effect on women's unemployment duration have none on men's ones. It is the case of the geographical environment, the fact of belonging to a large family and of having a technical education.

In general it must be said that the factors which seem to reduce average unemployment duration of young men are the French nationality of the father, a lower age, a higher level of education and finally 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, not having attended a technical school, to live in Paris, and again having started the unemployment spell in a favorable economic period.

These findings confirm the necessity of studying separately the two groups when trying to characterize their unemployment durations. Nevertheless it should be stressed that human, cultural and geographical factors appear to be useful characteristics in order to explain the behaviour of both the populations on the labour market, and this even if they affect their probability of leaving unemployment in a different way. Still it should be observed that information related either to family structure either to calendar time seems to be crucial when trying to characterize young people unemployment durations and their dynamics.

Annexe 1:*Tables and Graphs*

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

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

In %

Year	Young People	Adults
1970	1.2	0.5
1975	3.0	1.1
1980	5.8	1.7
1985	10.1	2.9
1990	11.4	3.1
1994	15.6	5.3

Source: Bruno and Cazes, 1997.

Table 2.3: Composition of Young People Unemployment by Qualifications

In %	**1983**	**1986**	**1992**	**1996**
Unemployment Rate of Non-Qualified Young People	25	31	28	36
Unemployment Rate of Qualified Young People	10.3	14.8	12.2	18.8

Source: Bruno and Cazes, 1997

Table 3.1: Descriptive Statistics

	MEN		WOMEN	
	Average	*Std.Error*	*Average*	*Std.Error*
Age of the individual (1)	23,77649	2,84985	24,32970	2,90333
Education Level (2)	15,30925	2,12931	15,64653	2,01845
Dummy variables :				
Dummy variable on the missing values of the education level (3)	0,04432	0,20590	0,05842	0,23464
Technical Education (4)	0,69364	0,46120	0,66832	0,47105
Father Nationality (5)	0,60308	0,48949	0,63762	0,48092
Large Family (6)	0,69557	0,46039	0,68713	0,46389
Region where living (7)	0,09730	0,29651	0,10891	0,31168
In School prior to the unemp. Spell $_{Yes=1}$ (8)	0,11079	0,31402	0,14257	0,34981
Training Prior to the unemp. Spell $_{Yes=1}$ (9)	0,08092	0,27285	0,14257	0,34981
Date of Entry in the unemp. Spell (10)				
1989=1	0,23507	0,42425	0,20198	0,40168
1990=1	0,29576	0,45660	0,30000	0,45848
1991=1	0,38439	0,48669	0,43663	0,49621
1992=1	0,08478	0,27869	0,06139	0,24016
Number of spells	**1038**		**1010**	

(1) It is the age of the young person in 1992, thus it is not a time-varying variable. People are aged between 18 and 29 in 1992.

(2) It is expressed in terms of theoretical age of end of studies. Each value of this variable corresponds then to the level of qualification attained by the young person when he/she left the schooling system. For instance a value of this variable equal to 18 states that the individual left the education system with a baccalauréat it does not mean on the contrary that he/she left it when being 18 years old. The minimum corresponds to 10 and thus almost to a primary education level and the maximum to 24, that is to a master degree. As to the procedure followed to correct for missing values see Section 3.2.

(3) This variable has been introduced to control for the adjustment adopted after having corrected for missing values; see again Section 3.2.

(4) It states if the individual has had a technical education: 1= Yes.

(5) Dummy variable stating the nationality of the father of the young person. It is equal to 1 when the father is of french-nationality and to 0 otherwise. It must be noticed that the nationality of the father is unknown, on average, for 0.1875 % of the sample. This is mainly due to the death of the father (almost 0.1333 % of the sample).

(6) It expresses the fact to belong or not to a large family, i.e. a family where the number of children is equal or greater than 3. It takes on the value 1 when the individual belongs to a large family and 0 otherwise.

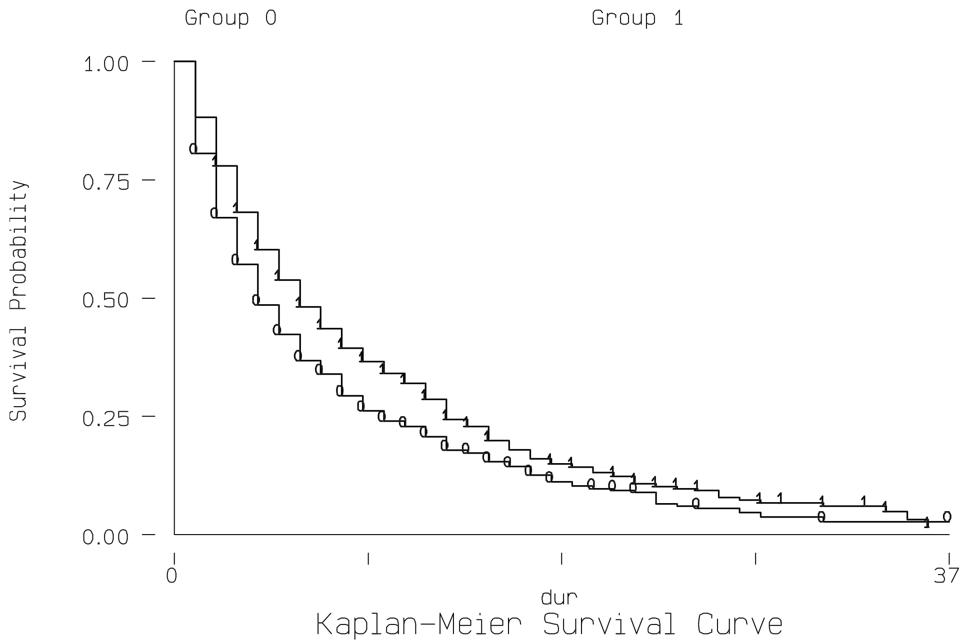
(7) It states if the individual lives in Paris or elsewhere in France. It is equal to 1 in the former case and to 0 in the latter.

(8) It states if the individual enters unemployment after having left the schooling system.

(9) It states if the individual enters unemployment after a training spell.

(10) It states the year in which the unemployment spell begun; 1989 is the year of reference.

Fig. 3.1: Kaplan-Meier Survival Rates



Group 0: men;
Group 1: women.

Table 6.1(a): Results of the estimation without unobserved heterogeneity - Men

	Semi-parametric	Weibull	Exponential
Constant	-1.8165** (.3970)	-1.6895** (0.3974)	-2.1535** (0.3918)
γ_2	-0.02155* (.09294)		
γ_3	-0.35034** (.1143)		
γ_4	-0.59745** (.1477)		
γ_5	-0.6674** (.1767)		
γ_6	-1.0489** (.2360)		
γ_7	-0.7554** (.2504)		
γ_8	-0.8361** (.2958)		
γ_9	-0.4754 (.2963)		
γ_{10}	-1.0331* (.4528)		
γ_{11}	-1.6149* (.7092)		
γ_{12}	-0.04757 (.4176)		
γ_{13}	-1.3735 (1.0005)		
γ_{14}	-0.5965 (.5841)		
Age of the individual	-0.03259** (.01403)	-0.03323** (0.01402)	-0.04111** (0.01406)
Education Level	0.069877** (.01832)	0.06914** (0.01829)	0.08326** (0.01811)
Dummy on the education level	-0.06139 (.2093)	-0.0523 (0.2091)	-0.0599 (0.2095)
Technical Education	0.1309 (.0876)	0.1324 (0.08762)	0.1414 (0.0879)
Father Nationality *French=1*	0.2039** (.07679)	0.2042** (0.07681)	0.2350** (0.07704)
Large Family Yes=1	-0.007668 (.08101)	-0.00636 (0.08098)	-0.00173 (0.08104)
Region where living *Paris=1*	-0.08372 (.12584)	-0.07854 (0.1256)	-0.10320 (0.1261)
In school prior to the unemp. spell *Yes=1*	-0.4669** (.1220)	-0.4636** (0.1219)	-0.5403** (0.1216)
Training Prior to the unemp. spell *Yes=1*	-0.06552 (.1326)	-0.06319 (0.1324)	-0.0954 (0.1326)
Year in which the unemp spell started *1990=1*	-0.1516 (.09063)	-0.1585 (0.0903)	-0.1651 (0.0906)
Year in which the unemp spell started *1991=1*	-0.3861** (.0955)	-0.38232** (0.0946)	-0.2995** (0.0943)
Year in which the unemp spell started *1992=1*	-0.6329** (.2131)	-0.6369** (0.2127)	-0.3831 (0.2116)
α		-0.31224** (0.04110)	0
$\sigma = \exp(\alpha)$ *(Duration Dependence)*		0.731803	1
Log-Likelihood	-2215.2765	-2220.8135	-2250.0769

(1) Standard Errors between parentheses

(2) **: significant at 2% (t -Student $\geq$ 2.326); *: significant at 5% (t -Student $\geq$ 1.96)

Table 6.1(b): Results of the estimation without unobserved heterogeneity - Women

	Semi-Parametric	Weibull	Exponential
Constant	-2.6251** (0.4566)	-2.5372** (0.4576)	-2.7696** (0.4526)
γ_2	0.0520 (0.1021)		
γ_3	-0.0856 (0.1184)		
γ_4	-0.1899 (0.1381)		
γ_5	-0.5232** (0.1806)		
γ_6	-0.3372 (0.1884)		
γ_7	-0.0876 (0.2067)		
γ_8	-0.0249 (0.2313)		
γ_9	-0.3215 (0.2993)		
γ_{10}	-0.6419 (0.3864)		
γ_{11}	-0.2484 (0.3633)		
γ_{12}	-0.8672 (0.5839)		
γ_{13}	-0.2675 (0.5066)		
γ_{14}	-0.5389 (0.4206)		
Age of the individual	-0.01447 (0.0152)	-0.01425 (0.0152)	-0.01561 (0.01525)
Education Level	0.07629** (0.0192)	0.076** (0.0192)	0.0797** (0.0191)
Dummy on the education level	0.00259 (0.1858)	0.00216 (0.1855)	0.00113 (0.1855)
Technical Education	-0.1757* (0.0867)	-0.1809* (0.0867)	-0.1974** (0.0867)
Father Nationality *French=1*	0.15188* (0.07966)	0.15516* (0.0792)	0.1700** (0.0796)
Large Family Yes=1	-0.2371** (0.08635)	-0.2410** (0.0829)	-0.2599** (0.0828)
Region where living *Paris=1*	0.2929** (0.10590)	0.2882** (0.1188)	0.3017** (0.1188)
In school prior to the unemp. spell *Yes=1*	-0.1282 (0.1203)	-0.1227 (0.1202)	-0.1176 (0.1204)
Training Prior to the unemp. spell *Yes=1*	-0.09094 (0.1078)	-0.0931 (0.1079)	-0.1036 (0.1079)
Year in which the unemp.spell started *1990=1*	-0.00704 (0.0972)	0.00049 (0.0962)	0.01904 (0.0962)
Year in which the unemp.spell started *1991=1*	-0.2715** (0.1055)	-0.2624** (0.1038)	-0.2068* (0.1028)
Year in which the unemp.spell started *1992=1*	-0.4820 (0.2945)	-0.4886 (0.2941)	-0.3364 (0.2908)
α		-0.1331** (0.04225)	0
$\sigma = \exp(\alpha)$ *(Duration Dependence)*		0.8754	1
Log-Likelihood	-2291.9266	-2297.9742	-2302.9327

(1) Standard Errors between parentheses

(2) **: significant at 2% (t -Student $\geq$ 2.326); *: significant at 5% (t -Student $\geq$ 1.96)

Table 6.2(a): Results of the estimation with unobserved heterogeneity - Men

	Semi-parametric	Weibull	Exponential
Constant	-1.8594** (.4420)	-1.7197** (.4217)	-1.9532** (.5078)
γ_2	-0.1538 (.1491)		
γ_3	-0.2369 (.2425)		
γ_4	-0.4439 (.3243)		
γ_5	-0.4755 (.4019)		
γ_6	-0.8312 (.4731)		
γ_7	-0.5005 (.5405)		
γ_8	-0.5522 (.6098)		
γ_9	-0.1579 (.6653)		
γ_{10}	-0.6833 (.7981)		
γ_{11}	-1.2472 (0.9912)		
γ_{12}	0.3716 (0.8922)		
γ_{13}	-0.9186 (1.3211)		
γ_{14}	-0.07829 (1.1566)		
Age of the individual	-0.03466* (.01574)	-0.03399* (.01469)	-0.03905* (.01768)
Education Level	0.07713** (.0242)	0.07192** (.02088)	0.0812** (.02367)
Dummy on the education level	-0.05734 (.2268)	-0.05004 (.2162)	-0.0354 (.2577)
Technical Education	0.1459 (.0993)	0.13826 (.09261)	0.1687 (.1107)
Father Nationality French=1	0.2236** (.0918)	0.2117** (.0831)	0.2627** (.0969)
Large Family Yes=1	0.000846 (.09102)	-0.000373 (.08467)	0.020119 (.1043)
Region where living Paris=1	-0.0858 (.1384)	-0.07994 (.1307)	-0.0949 (.1595)
In school prior to the unemp. spell Yes=1	-0.5264** (.1715)	-0.4863** (.1444)	-0.6351** (.1527)
Training Prior to the unemp. spell Yes=1	-0.07179 (.1471)	-0.0651 (.1382)	-0.07902 (.1709)
Date of Entry in the unemp. spell 1990=1	-0.1641 (.1044)	-0.1639 (.0960)	-0.2069 (.1198)
Date of Entry in the unemp. spell 1991=1	-0.4045** (.1096)	-0.3930** (.1034)	-0.4485** (.1214)
Date of Entry in the unemp. spell 1992=1	-0.6535 (.2244)	-0.6448** (.2175)	-0.6776** (.2383)
α		-0.27263 (.1697)	0
σ = exp(α) (Duration Dependence)		0.76137	1
σ^2 *(Unobserved. Heterogeneity)*	0.1554 (0.2939)	0.06014 (0.1881)	0.45473** (0.0758)
Log-likelihood	-2215.2765	-2220.7599	-2221.6191

(1) Standard Errors between parentheses

(2) **: significant at 2% (t -Student $\geq$ 2.326); *: significant at 5% (t -Student $\geq$ 1.96)

Table 6.2(b): Results of the estimation with unobserved heterogeneity - Women

	Semi-parametric	Weibull	Exponential
Constant	-2.6258** (.4573)	-2.5705** (.4862)	-2.6363** (.5071)
γ_2	.05200 (.1024)		
γ_3	-0.0856 (.1194)		
γ_4	-.1899 (.1398)		
γ_5	-.5232** (.1828)		
γ_6	-.3372 (.1908)		
γ_7	-.0876 (.2106)		
γ_8	-.02491 (.2364)		
γ_9	-.3214 (.3041)		
γ_{10}	-.6419 (.3906)		
γ_{11}	-.2485 (.3678)		
γ_{12}	-.8674 (.5872)		
γ_{13}	-.2677 (.5125)		
γ_{14}	-.5391 (.4278)		
Age of the individual	-.01449 (.01523)	-.01544 (.01614)	-.01689 (.01694)
Education Level	.07640** (.0193)	.0801** (.02203)	.0829* (.02175)
Dummy on the education level	.00265 (.1858)	.0074 (.1940)	.01382 (.2045)
Technical Education	-.1757* (.0868)	-.1797* (.0912)	-.1798 (.09705)
Father Nationality *French=1*	.1519 (.07978)	.1537 (.0839)	.1524 (.0895)
Large Family *Yes=1*	-.2370** (.08317)	-.2537** (.09124)	-.2699** (.09371)
Region where living *Paris=1*	.2929** (.1193)	.3109** (.1344)	.3404** (.1360)
In school prior to the unemp. spell *Yes=1*	-.1284 (.1207)	-.1478 (.1369)	-.1822 (.1352)
Training Prior to the unemp. spell *Yes=1*	-.0909 (.1079)	-.1011 (.1156)	-.1145 (.1221)
Year in which the unemp.spell started *1990=1*	-.0071 (.0973)	-.0109 (.1052)	-.0236 (.1115)
Year in which the unemp.spell started *1991=1*	-.2715** (.1058)	-.2742** (.1114)	-.2829** (.1168)
Year in which the unemp.spell started *1992=1*	-.4821 (.2948)	-.4987 (.2999)	-.5002 (.3062)
α		-0.07997 (0.1187)	0
$\sigma = exp(\alpha)$ *(Duration Dependence)*		0.92313	1
σ^2 *(Unobserved. Heterogeneity)*	.00000431 (0.000087)	0.08834 (0.1867)	0.208114 (0.07354)
Log-likelihood	-2291.9266	-2297.8533	-2298.0665

(1) Standard Errors between parentheses

(2) **: significant at 2% (t -Student ≥ 2.326); *: significant at 5% (t -Student ≥ 1.96)

Table 6.3: Hausman (1978) test [(1)]

	MEN	WOMEN
	Without Unobserved Heterogeneity	
Semi-Parametric / Exponential $\cong\chi^2_{13}$	33.8433 (0.9987) => H_0 rejected	11.3969 (0.4224) => H_0 not rejected
Semi-Parametric / Weibulll $\cong\chi^2_{13}$	7.1405 (0.1052) => H_0 not rejected	1.0559 (0.00005) => H_0 not rejected
	With Unobserved Heterogeneity	
Semi-Parametric / Exponential $\cong\chi^2_{13}$	1.9502 (0.0019) => H_0 not rejected	4.6424 (0.01775) => H_0 not rejected
Semi-Parametric / Weibulll $\cong\chi^2_{13}$	20.1985 (0.9086) => H_0 not rejected	21.3337 (0.9334) => H_0 not rejected

(1) In the Hausman (1978) test under the null hypothesis (H_0) both estimators are consistent; under the alternative (H_1) only the semi-parametric are consistent. (p-values in parentheses)

Table 6.3: Likelihood ratio tests[(2)]

	MEN	WOMEN
	Without Unobserved Heterogeneity	
Semi-Parametric / Exponential $\cong\chi^2_{13}$	69.6008 (1.0000) => H_0 rejected	22.0122 (0.9448) => H_0 not rejected
Semi-Parametric / Weibulll $\cong\chi^2_{12}$	11.074 (0.4774) => H_0 not rejected	12.0952 (0.5619) => H_0 not rejected
Weibull / Exponential $\cong\chi^2_{1}$	58.5268 (1.0000) => H_0 rejected	9.917 (0.9984) => H_0 not rejected
	With Unobserved Heterogeneity	
Semi-Parametric / Exponential $\cong\chi^2_{13}$	12.9826 (0.5508) => H_0 not rejected	12.2798 (0.4952) => H_0 not rejected
Semi-Parametric / Weibulll $\cong\chi^2_{12}$	11.2642 (0.4936) => H_0 not rejected	11.8534 (0.5425) => H_0 not rejected
Weibull / Exponential $\cong\chi^2_{1}$	1.7184 (0.8101) => H_0 not rejected	0.4264 (0.4862) => H_0 not rejected

(2) In the Likelihood Ratio test under the null hypothesis (H0) the unconstrained model - i.e. the semi-parametric - does not ameliorate the fit; under the alternative (H1) it does. (p-values in parentheses)

Table 6.5: Models retained

	MEN	WOMEN
	Without Unobserved Heterogeneity	
Model retained	WEIBULL	WEIBULL
	With Unobserved Heterogeneity	
Model retained	EXPONENTIAL	EXPONENTIAL

Fig. 6.1: Hazard Rate (without unobserved heterogeneity) -Men

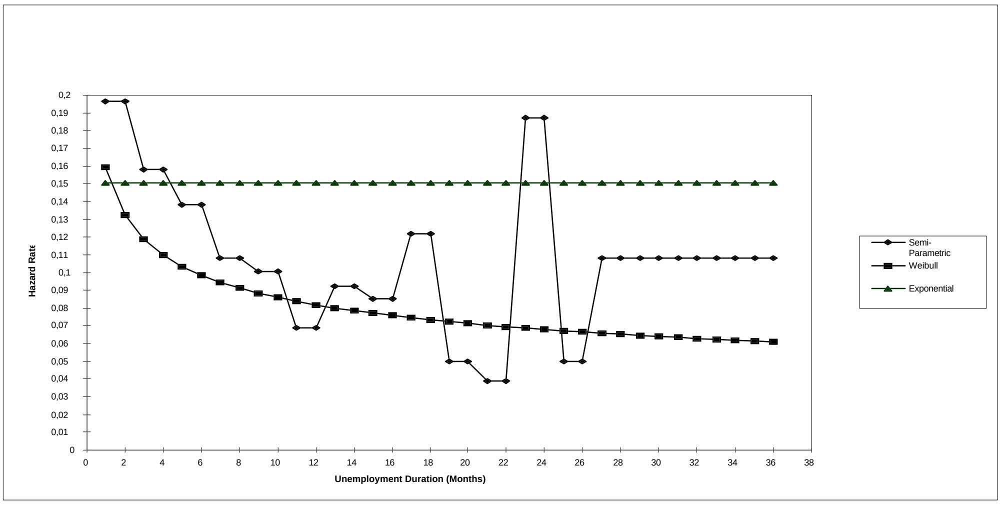


Fig. 6.2: Hazard Rate (without unobserved heterogeneity) -Women

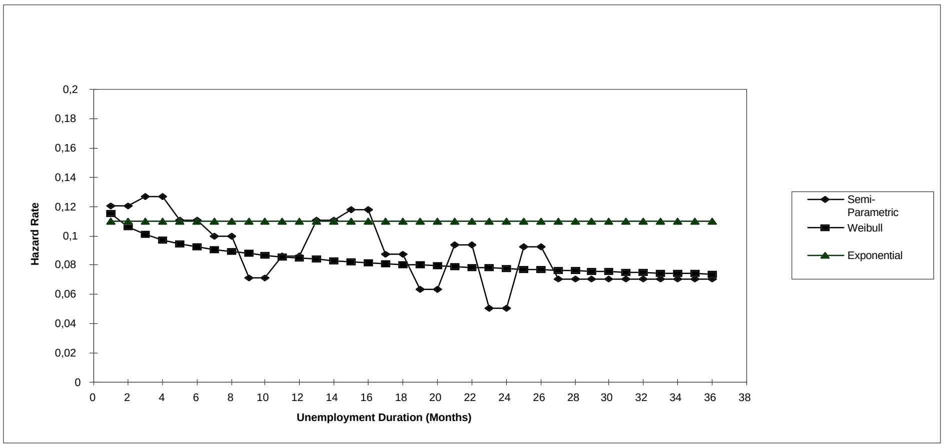


Fig. 6.3: Hazard Rates of Men and Women (without unobserved heterogeneity)

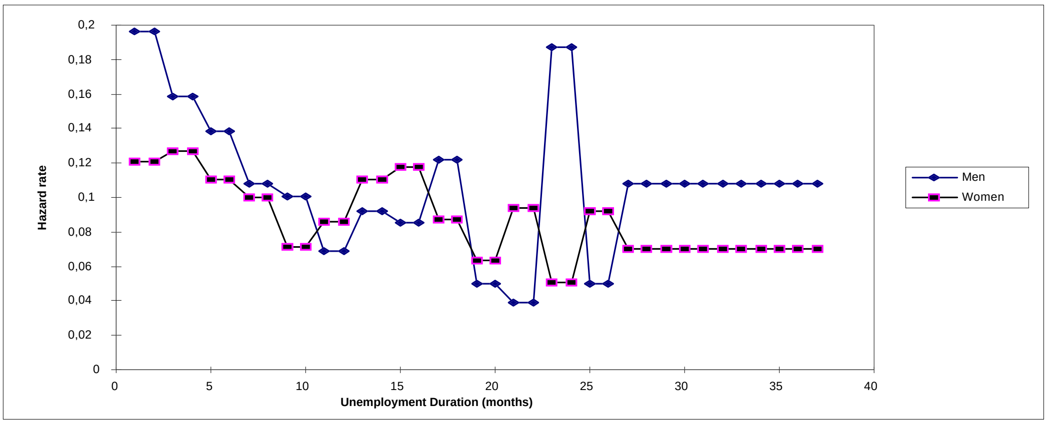


Fig. 6.4: Hazard Rate (with unobserved heterogeneity) -Men

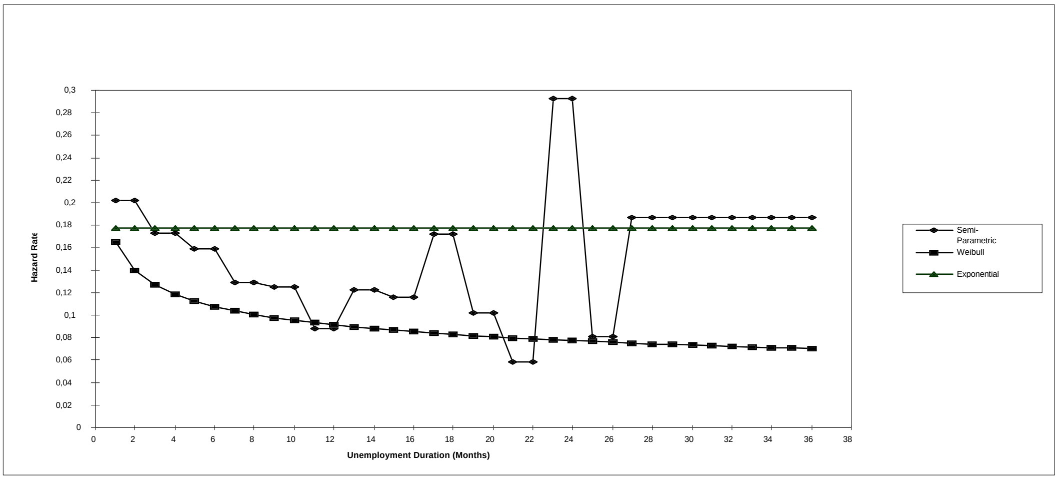
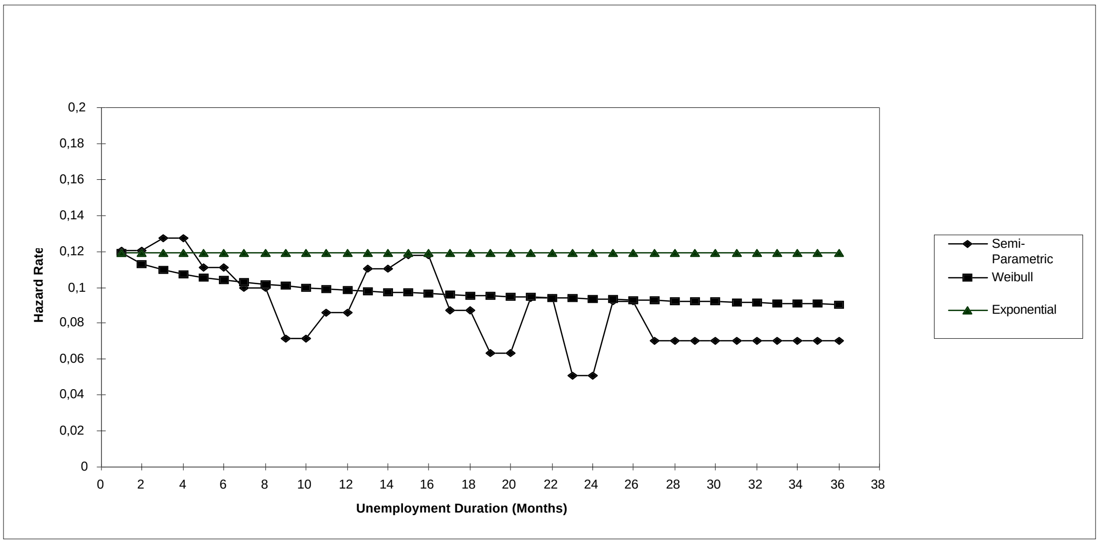


Fig. 6.5: Hazard Rate (with unobserved heterogeneity) -Women



Annexe 2: *Parametrization of the gamma function*

The density is given by (see Blossfeld, Hamerle and Mayer,1989; Lancaster 1990; Stewart,1996).

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

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

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