# THE TRANSITION TO WORK FOR ITALIAN UNIVERSITY GRADUATES: DETERMINANTS OF THE TIME TO OBTAIN THE FIRST JOB.


**by**

**Dario Pozzoli**

Università Cattolica, Defap


May, 2005


## Abstract

This study investigates the hazard of exit from unemployment for Italian graduates. The analysis is in particular focused on the transition from university to work, taking into account the graduates' characteristics and the effects relating to degree subject. It is used a large data set from a survey on job opportunities for the 1998 Italian graduates. The paper employs both parametric and semi-parametric discrete-time single risk models to study employment hazard. Alternative mixing distributions have also been used to account for unobserved heterogeneity. The results obtained indicate that there is evidence of positive duration dependence after a short initial period of negative duration dependence. In addition, competing risk model with unobserved heterogeneity and semi-parametric baseline hazard have been estimated to characterize transitions out of unemployment. Results reveal that the use of an aggregate approach sometimes compound distinct and contradictory effects.

## 1. Introduction

The problem of high unemployment rates for young people has been featuring top of public policy discussion and of government policy-making in Italy in recent years. The difficulties of getting a job for young people are so relevant that we can consider youth unemployment as a distinct and stable feature of Italian unemployment. The outstanding youth unemployment incidence constitutes a common element of Southern European labour markets. In Italy, youths of age between 15 and 26 years represent about 40% of the total population searching for a job in 1998[1]. This situation is comparable only to the other Mediterranean countries (Spain, Greece, Portugal). The particularity of Italian situation is evident by the fact that even in countries where the general unemployment rate is close to the Italian one (France), the youth unemployment incidence is much more lower (22%)[1]. Another important feature of Italian youth unemployment is that it is above all concentrated among women and in the South. As matter of fact, considering the age group from 15 to 29 years, the female unemployment is 1.5 times the male one and the youth unemployment rate in the southern regions is three times as much as the one in the North of Italy[2]. Moreover, the youth unemployment rate increase among the youths with a university degree. In particular the university graduates face high unemployment rates especially in the first years after graduation[3]. This is not true if we consider high school graduates who have more chances of getting the first job, mainly in the northern regions. This suggests a problematic transition from school to work for individuals who get high levels of education. Could these difficulties be explained by the fact that the Italian educational system produces too many university graduates? The answer is certainly negative, because Italy is one of countries where the percentage of university graduates is the lowest (8%, in 1995)[4]. The most plausible explanations for the difficult transition from university to work of Italian graduates are:

- possible mismatch between labour demand and supply;
- excessive insiders' protection and new entrants' relegation to temporary jobs or unemployment;
- shortages of incentive and flexible active labour market policies targeted to youth unemployment;
- insufficient economic growth with a limited occupational content;

[1] Source: Censis, Rapporto sulla situazione del Paese, anno 1999.
[2] Source: elaborazioni su dati ISTAT, rilevazione delle forze lavoro, primo trimestre 1999.
[3] The unemployment rate of university graduates two years and 5-6 years after graduation are respectively 27% and 13.3% (Source: ISTAT, rapporto annuale 1998).
[4] The same percentage for US and UK are respectively 24% and 12% (Source OCSE, Regard sur l'education 1997).

- manufacturing system based on non-innovative small and middle-sized enterprises demanding more frequently technical and executive staff than personnel with high education.

The problems of youth labour market highlighted previously explain why the analysis of the transition from university to labour market has received increasing attention in the labour micro-econometric literature. Most empirical studies on this issue are based on descriptive statistical methods (e.g. Centre for Educational Research and Innovation (1997) and Tronti and Mariani (1994)). Simple regression models have also been used to study the probability of being employed (e.g. Lynch (1987), Boero at al. (2001)). However, very few studies investigate the problem of the time to obtain a job. These exceptions are based on survival analysis, as this can deal with the censoring problem easily through appropriate specification of the sample likelihood. The works of Layder et al. (1991), Dolton et al. (1993) and Santoro and Pisati (1996) employ a continuous time Cox model. Firth et al.(1999) used a discrete time survival model while Mealli and Pudney (1999) proposed an alternative approach with a transition model. Biggeri, Bini and Grilli (2000) evaluate the effectiveness of educational institutions with respect to job opportunities using a multilevel discrete time survival model.

Most of these studies however does not explicitly take into account of unobserved heterogeneity between graduates. Many analyses (Lancaster, 1979; Nickell, 1979; Lynch, 1985, and Moffit 1985) have emphasized the importance of incorporating unmeasured heterogeneity into the specification of the distribution for unemployment duration because unmeasured heterogeneity leads to biased inference in duration models.

The purpose of this paper is to extend the current literature based on Italy’s data by incorporating heterogeneity into the econometric specification to study the factors that determine the transition from university to work as well as to evaluate the effectiveness of university and course programmes with respect to the labour market outcomes of their graduates. Semi-parametric and parametric estimation methods are used. The results obtained indicate that there is evidence of positive duration dependence after a short initial period of negative duration dependence. Accounting for unobserved heterogeneity does matter, but the main finding to duration dependence remains unchanged. With regards to the effects of covariates, older and female graduates, those who graduated in Humanities and Social sciences, those who had parents with the lowest level of education, those males who did their service after their degree and finally those who live in southern and central Italy are found to have particularly lower hazard of getting their first job.

Another novelty of this paper resides in its identification of 2 destination states, namely, open-ended employment and fixed-term contracts. Results from competing risk model reveal that the use of an aggregate approach sometimes compound distinct and contradictory effects. Thus, for example, the probability of finding employment in open-ended contracts is increasing with the level of education of parents. But these effects are completely absent if we consider exit to fixed-term contracts. Female graduates have a higher hazard of exit to fixed contracts but a lower hazard of exit to open-ended employment compared to their male counterparts. Those who live in the Centre of Italy are less likely to enter open-ended employment than their Northern Italian counterparts, this is not true if we consider exit to fixed term contract.

This study has six parts and has the following structure. In section 2, I outline the economic model of unemployment duration. Section 3 is devoted to the description of the data and sample used in the empirical exercise carried out in this study. Section 4 gives an account of the econometric specifications and methods of estimation used for the purpose of studying the time to first job. Section 5 discusses the estimation results obtained and the final section concludes the paper.

## 2. The basic model

The highly stylized model described below serves as a basic theoretical framework for the empirical analysis developed in the subsequent sections. Suppose that all individuals occupy only two states: employment and unemployment. For concreteness, I concentrate only on the transition from unemployment to employment. State e is employment and u is unemployment. The formal structure I use allows the worker to change states at any time t. This worker is assumed to be actively looking for employment. He seeks to maximize the expected present value of income, discounted to the present over an infinite horizon at rate $\rho$[5]. The income flow while unemployed, net of search costs, is $b_t$ and it depends on the elapsed duration. He receives job offers while unemployed according to a Poisson process with parameter $\lambda_t$ which is a function of the duration of unemployment. This implies that the probability of obtaining an offer in a given interval of time is proportional to the length of that interval. A job offer is summarized by a wage rate w. Jobs have many characteristics, including wages, hours, benefits, working conditions, and amiability of co-workers and supervisors. However it is assumed that the wage is the most important-the item on which the worker bases the decision to accept or decline employment. Successive job offers received over the course of a spell of unemployment are realizations from a known[6] exogenous

[5] To facilitate the analysis the worker is assumed to be risk neutral: income and utility are equivalent. Hence it is possible to investigate the individual attempting to maximize the expected present discount value of income.

[6] This means that the worker does not know where which jobs are available , but does know the general characteristics of the local labour market.

time-variant[7] wage offers distribution with finite mean and variance, cumulative distribution function $F_t(w)$ and density $f_t(w)$. The worker does not have an expectation of the types of offers made by particular firms, hence a random search occurs. Once rejected, an offer cannot be recalled. When accepted, a job will last forever.

Supposing that the parameters are allowed to vary over the interval of time, t=[0, T], in a deterministic way, and job searchers have rational expectations[8], the Bellman's functional equation becomes:

$$V(w) = \max\left\{V^e(w); \frac{1}{\rho}\left[\frac{dV^u(t)}{dt} + b(t) + \lambda(t)\int_0^\infty V^e(w)dF_t(w)\right]\right\} \quad (2.1a)$$

where $V^u$ is the maximum expected value of being unemployed and $V^e(w)$ is the utility associated with being employed. The latter is a function of the wage paid and it is reasonable to assume that $dV^e(w)/dw>0$, higher wages are preferred to lower. Precisely $V^e(w)$ is equal to $\int e^{-\rho t} w\, dt = w/\rho$ the value of accepting an offer w. The maximization is taken over two actions: (1) accept the wage offer w and work forever at wage w or (2) reject the offer, receive b(t) and $\frac{dV^u(t)}{dt}$ this period and draw a new offer w from distribution $F_t$ next period. Because the value of employment, w/ρ, is an increasing function of the wage offer, there must be values of w for which employment is an attractive option; otherwise the worker would never enter the labour market. The must also be values of w for which employment is not an attractive option, otherwise the first wage offer would automatically be accepted.

The Bellman equation (2.1a) for the worker's problem can also be written as an optimal stopping rule for work, such that,

$$\rho V^u(t) = \frac{dV^u(t)}{dt} + b(t) + \lambda(t)\left\{\int_0^\infty \max\left[0, V^e(w) - V^u(t)\right]dF_t(w)\right\} \qquad (2.1b)$$

This equation has a familiar structure of asset flow value equations (see e.g. Pissarides, 1990). The return of the asset $V^u$ in a small interval around t equals the sum of the appreciation of the asset in

[7] This implies that the worker who is unemployed for 30 weeks, for example, doesn't face exactly the same job prospects as the newly unemployed worker. Thus, the search strategy does depend on time spent unemployed.

[8] Job searchers have rational expectations in the sense that they correctly anticipates changes of parameters (Van den Berg, 1990): non-stationarity with anticipation. It is also assumed that these parameters are constant for all sufficiently high t. The latter implies that the optimal strategy is also constant for sufficiently high t.

this interval, the instantaneous utility flow in this interval, and the expected excess value of finding a job in this interval. When an offer of w arrives at t then there are two options : (i) to reject it (excess value zero), and (ii) to accept it (excess value w/ρ-$V^u$).

It is clear that the optimal strategy of the worker is a reservation wage function w*(t) that gives the reservation wage at time t. Using that w*(t)=ρ$V^u$(t), it follows that:

$$w^*(t) - b(t) = \frac{1}{\rho}\frac{dw^*(t)}{dt} + \frac{\lambda(t)}{\rho}\int_{w^*(t)}^{\infty}(w - w^*(t))dF_t(w) \quad (2.2a)$$

where the left side of (2.2a) is the cost of searching one more time when an offer w*(t) is in hand while the right side represents the expected benefit of searching one more time in terms of the expected present value associated with drawing w>w*(t). Therefore the reservation wage w*(t) is such that the marginal benefit of an additional search is equal to its marginal cost.

Alternatively, equation (2.2a) can be written as:

$$\frac{dw^*(t)}{dt} = \rho w^*(t) - \rho b(t) - \lambda(t)\int_{w^*(t)}^{\infty}(w - w^*(t))dF_t(w) \quad (2.2b)$$

This differential equation has a unique solution for w*(t), given the boundary condition that follows from the assumption that the model is stationary for all sufficiently high t.

The unemployment duration distribution for the above model is fully characterized by the time-varying hazard rate at duration t of unemployment, h(t), which is given by,

$$h(t) = \lambda(t)(1 - F(w^*(t), t)) \quad (2.3)$$

The survivor function for t periods of unemployment is equal to:

$$\Pr(t > T) = \exp(-\int_0^t h(u)du \quad) \quad (2.4)$$

and the density of the completed duration t is,

$$g(t) = \lambda(t)(1 - F(w^*(t), t) \exp(-\int_0^t \lambda(u)(1 - F(w^*(u), u) du) = h(t) \exp(-\int_0^t h(u) du) \quad (2.5)$$

The likelihood function of a sample of durations for i unemployed workers, ($t_i$, i=1,……,I), with no incomplete spells of unemployment, is given by:

$$L(b(t), \lambda(t), \rho, F(w^*(t), t) \mid t_1, ......., t_I) = \prod_{i-1}^{I} h(t_i) \exp(-\int_0^{t_i} h(u) du) \quad (2.6)$$

Clearly, using only duration data, the only identified parameter is the hazard rate, h(t), and none of the structural parameters of the search model is identified (Flinn and Heckman, 1982).

In this setting the aggregate hazard rate may be duration dependent not only because of heterogeneity of the hazard rate among individuals but also because the environment (parameters) at individual level is not stationary. For example, the amount of unemployment benefits ($b_t$) depends on the elapsed duration and they are of limited duration: in this case it can be shown that the reservation wage w*(t) declines (and the hazard therefore rises) up to the date of exhaustion. Time variance of the arrival rate $\lambda_t$ and the offer distribution F(.) over the entire duration of a spell might also be realistic. It might be argued that employers interpret a long spell of unemployment as a signal that a worker is a “lemon”, for example, in which case the arrival rate might be expected to decline as a spell continues. Human capital might also diminished by the time out of work. Again, a decline in the arrival rate of offers might be expected and the offer distribution might shift down or change shape, as well. Alternatively, a worker (feeling either discouraged or desperate) may adjust his or her search effort and methods over the course of a given spell. A worker may look initially only into the best jobs available for a person with his or her skills, but look into less desirable opportunities later in a spell. In either of these cases, the distribution of offers would effectively vary with duration and the arrival rate might rise or decline or do both as a result of such strategy changes. All of these considerations suggest that incorporating nonstationarity into the model is appropriate.

Now consider again equation (2.3). It would obviously be useful for any empirical analysis of unemployment durations to be able to separate between the two factors at the right-hand side, i.e. to assess their relative magnitude for different types of individuals, as well as to assess the size of policy effects on them. However, descriptive analysis of unemployment durations developed in this paper simply restrict attention to variation of h itself over time and across individuals with different observed characteristics x. The hazard function in particular is specified as a multiplicative function of t, x. This defines the Proportional Hazard model, which is an ad hoc descriptive statistics for h. In obvious notation:

$$h(t,x) = h_t(t)\exp(x'\beta) \quad (2.7)$$

This empirical approach raises an important issue. According to (2.3) the hazard rate h at t depends on all structural parameters in a heavily non-linear fashion by way of the current reservation wage w*(t). Even if these structural parameters are simple functions of t and/or x, this leads to a non-proportional expression for h. Because the Proportional Hazard model parameters are not structural parameters, a causal interpretation of the reduced-form estimates is problematic. The hazard is proportional in t and x in the special case where $\rho \rightarrow \infty$. In that case workers do not care about the future and even though they have information on future changes, this does not affect his optimal strategy. The exit rate out of unemployment is:

$$h(t,x) = \lambda(t,x)F_t(b(t,x) \mid x) \quad (2.8)$$

if $\lambda(t,x)$ varies with t (e.g. because the long term unemployed are stigmatized) but not with x, and F and b vary with x but not with t, the hazard is proportional in t and x. Alternatively, if F and b do not depend on either t or x and $\lambda$ is proportional in t and x, then the hazard is proportional as well.
Concluding the proportionality restriction of PH model cannot in general be justified on economic-theoretical grounds. However, if the optimal strategy is myopic (e.g. because the discount rate is infinite), then this restriction follows from non-stationary job search model described above.

## 3. Data

In 2001, ISTAT (see ISTAT, 2001), conducted the fourth survey on the transition of Italian graduates into the labour market. The objective of the survey is to analyse the occupational position of graduates three years after the completion of their university studies. Accordingly, the 2001 survey is conducted on those graduating in 1998. The graduate population of 1998 consisted of 105,097 individuals (49,393 males and 55,704 females). The ISTAT survey was based on a 25% sample of these students and was stratified on the basis of university attended, degree course taken and by sex of the individual student. The response rate was about 67%, yielding a data-set containing information on 20,844 graduates. As a consequence the sample used in the present analysis is not properly representative of the total population (although the ISTAT used a weighting system for post-stratification to reduce the bias due to the non-response); so, the results presented in the following sections should be considered with caution. The data contain information on: the curriculum studied up to graduation in 1998, the occupational status and related work details by 2001, the search processes used between 1998 and 2001, the student's family background and personal characteristics.

For the present analysis, the sample of 20,000 records is reduced to 12,233 records by eliminating the individuals who: (i) started their current jobs while at university, since their post-graduation choices might be not comparable with those of the rest of the sample; (ii) declared that they were not interested in finding a job; (iv) did report the information necessary for computing unemployment duration and (v) didn't go on to further education (master, phd, second degree, school of specialization).

In the present paper, the object of interest is the time to obtain the first job. The latter is grouped in quarters, because the survey indicates only the quarter of graduation and not its precise month. Here, it is possible to distinguish between temporary and permanent jobs, but it is not provided information on the contract type (part-time, full-time). The questionnaire allows us to make this classification only with respect to the job held at the date of the interview, which is not necessarily the first job. The graduates in 1998 were interviewed in December 2001, so the observable time to obtain their first job ranges from 1 to 16 quarters. The time for the graduates who were still unemployed at the date of interview is right censored and assumes a value between 12 and 16 depending on the quarter in which the individuals received their degree. The definitions of covariates used in the analysis are reported in the appendix along with their sample means. Concerning the covariates the following clarifications should be made : (1) there are not time-varying covariates; (2) the dummy variable "military service" simply indicates whether the service was done after the degree as opposed to either being done before the degree or that the student was exempted from it; (3) the sample employed in the analysis has 15 groups of course programmes which I have further grouped into 4 main categories[9]: Scientific, Engineering, Humanities, Social sciences; (4) the geographical dummies refer to the University regions; (5) the dummy "mobility" indicates whether the student transferred in another region to attend university; (6) parental background is described by 7 categorical variable summarizing both parents' educational level and by father's occupation; (7) as indicator of academic performance I used the variable "final mark" (ranging from 66 to 110). The distribution of final mark is highly right skewed. This suggest that there is a ceiling effect which weakens the correctness of this covariate as an indicator of academic ability. To compensate partially for the previously mentioned deficiencies of the final mark, I used also, as measures of ability, the score at high school and the type of high school (general, vocational/technical or other)

## 4. Model specifications and methods of estimation

That the duration variable of interest (time to obtain the first job) is measured in quarters means that the appropriate approach to modelling the duration of unemployment is the discrete-time hazard model. The estimation of discrete-time duration models requires expanded or person-period data set organized in such a way that there will be as many data rows for each individual in the sample as there are time intervals over which the individual in question is at risk of experiencing the event of interest (Jenkins 1997, 2003)- first job here. Following Meyer (1990), the discrete time hazard of exiting the state of unemployment can be modelled using the discrete-time proportional hazards model (PH specification, thereafter). In particular, the hazard of employment in the $j^{th}$ quarter, h(tj), for individual i with a vector of covariates, x, having spent t quarters in unemployment and given that employment has not occurred before tj-1 can be given by:

$$h_{ij} = 1 - \exp(-\exp(\gamma_j(t) + (x_i\beta))), \quad \text{where } \gamma_j(t) = \int_{-\infty}^{\infty} h_0(u)du \quad (4.1)$$

$\gamma_j(t)$ represents the baseline hazard which can be specified either parametrically or semi-parametrically.

[9] The grouping in particular is the following: Scientic (chemistry, pharmacy, biology, agricultural, geology); Engineering (engineering, architecture); Social sciences (political sciences, sociology, law, economy and statistics); Humanities (literature, foreign languages, psychology, pedagogy).

I have assumed both parametric specification (log-polynomial) and a semi-parametric one (piecewise constant)[10]. Rearranging (9) gives what is known as the complementary log-log transformation of the conditional probability of exiting the state of unemployment at time tj as:

$$\ln(-\ln(1-h_{ij}(t_j \mid x_i)) = x_i{}' \beta + \gamma_j(t) \qquad (4.2)$$

Given this complementary log-log transformation, the parameter β is interpreted as the effect of covariates in x on the hazard rate of employment in interval j, assuming the hazard rate to be constant over the jth interval. To check the correctness of the PH specification, I have also estimated a discrete time logistic model, also known as proportional odds model. This specification (originally developed only for the intrinsically discrete survival times and later applied also on interval-censored data) assumes that the relative odds of making a transition in quarter j, given survival up to end of the previous quarter, is:

$$\frac{h_{ij}}{1-h_{ij}} = \left[\frac{h_j(0)}{1-h_j(0)}\right]\exp(\beta' x_i) \quad (4.3)$$

where $h_{ij}$ is the discrete time hazard rate for quarter j and $h_j(0)$ is the corresponding baseline hazard arising when $x_i$=0. The relative odds of making a transition at any given time is given by the product of two components: (i) a relative odds that is common to all individuals, and (ii) an individual-specific scaling factor. It follows that:

$$\log it\left[h_{ij}\right] = \log\left[\frac{h_{ij}}{1-h_{ij}}\right] = \alpha_j + \beta' x_{ij} \quad (4.4)$$

where $\alpha_j$=log[$h_j$(0)/1-$h_j$(0)]. We can write this expression, alternatively, as

$$h_{ij} = \frac{1}{1+\exp(-\alpha_j - \beta' x_i)} \quad (4.5)$$

[10] Several intervals have the same hazard, rather than differing in every interval. In this study the quarterly time period has been regrouped to get only 5 times periods. The rearranged time periods are: Quarter 1, Quarter 2-3, Quarter 4-7, Quarter 8-11, Quarter >12.

This is the logistic hazard model and, given its derivation, has a proportional odds interpretation. As in the cloglog case, I specify the baseline hazard $\alpha_j$ both parametrically and semi-parametrically ($\alpha_j$ is an interval-specific parameters).

The log-likelihood function for the sample of individuals in this study can be given by:

$$\log L = \sum_i^n \sum_j^t y_{it} \log(\frac{h_{ij}}{1-h_{ij}}) + \sum_i^n \sum_j^t \log(1-h_{ij}) =$$

$$= \sum_{i=1}^n \sum_{j=1}^t \left[ y_{it} \log h_{ij}(t \mid x) + (1-y_{ij}) \log(1-h_{ij}(t \mid x) \right] \quad (4.6)$$

It is well established in the duration literature that not accounting for unobserved heterogeneity[11] might lead to biased estimates of the baseline hazard as well as the covariate effects on the hazard of exit from the state of unemployment (Heckman and Singer, 1984; Lancaster, 1990). Taking this into account, an attempt has been made in this study to control for unobserved heterogeneity. The standard practice in the literature is to introduce a positive-valued random variable (mixture), v, into the hazard specification.

In the context of the proportional hazard approach, the augmented hazard function (MPH, thereafter), which incorporates a multiplicative mixture term, is given by:

$$\ln(-\ln(1-h_{ij}(t_j, x_i \mid v)) = x_i'\beta + \gamma_j(t) + u_i \qquad (4.7)$$

where $u_i = \log(v_i)$. It is not possible to estimate the values of v themselves since, by construction, they are unobserved. Or equivalently, there are as many individual effects as individuals in the data set, and there are not enough degrees of freedom left to fit these parameters. However if we suppose that the distribution of v has a shape whose functional form is summarized in terms of only a few key parameters, then it is possible to estimate those parameters with the available data. So after having specified a distribution for the random variable v, we derive the "frailty" survivor corresponding to this mixture distribution and we write the likelihood function so that it refers to the original parameters and mixing distributional parameters rather than each v[12]. In the discrete-time case, the individual likelihood contribution that incorporates the unobserved heterogeneity term is:

---

[11] The unobserved individual characteristics are usually referred to as "frailty" in the bio-medical sciences.

[12] This is known as "integrating out" the random individual effect.

$$L_i(\beta,\gamma,\Delta)=\int_{-\infty}^{+\infty}(\prod_{j}^{t} h_j(t,x_i \mid u_i)^{y_{ij}}(1-h_j(t,x_i \mid u_i))^{1-y_{ij}})g_u(u_i)du \quad (4.8)$$

where $\Delta$ is the vector of unknown parameters in $g_u(u_i)$. The unobserved heterogeneity term is assumed to be independent of observed covariates, $x_i$ , and the random duration variable, T, and have density $g_u(u_i)$. In the absence of theoretical justification for using one or the other approach, I assume two alternative parametric distribution: Gamma and Normal. If v has a Gamma distribution with unit mean and variance $\sigma^2$, as proposed by Meyer (1990), there is a closed form expression for the frailty survivor function[13]:

$$S(t,X \mid \beta,\sigma^2)=\left[1-\sigma^2 \ln S(t,X)\right]^{-\frac{1}{\sigma^2}} \quad (4.9).$$

With an inflow sample with right censoring, the contribution to the sample likelihood for a censored observation i with spell length j intervals is $S(t_j, x_i| \beta, \sigma^2)$ and contribution of someone who makes a transition in the jth interval is $S(t_j\text{-}1, x_i \mid \beta, \sigma^2)$- $S(t_j, x_i| \beta, \sigma^2)$, with the appropriate substitution made. Alternatively, I suppose that u has a Normal distribution with mean zero. In this case, there is no convenient closed form expression for the survivor function and hence likelihood contributions: the “integrating out” must be done numerically.

Finally I have also distinguished between two exit modes out of unemployment (fixed-term contracts and open-ended contracts) estimating an independent competing risks model (ICR, thereafter). Hence I have defined the cause-specific hazard function to destination fc (fixed contracts) and to destination oc open-ended contracts as:

$$h_{ij}^{fc}=1-\exp\left[-\int_{t_j-1}^{t_j}\theta_{fc}(t)dt\right] \qquad (4.13)$$

$$h_{ij}^{oc}=1-\exp\left[-\int_{t_j-1}^{t_j}\theta_{oc}(t)dt\right] \qquad (4.14)$$

where $\theta_{fc}$ and $\theta_{oc}$ are the underlying destination-specific continuous time hazard. The overall discrete hazard and the survivor function for exit to any destination for tj are instead given by:

$$h_{ij} = 1 - \left\{ \left[ 1 - h_{ij}^{fc} \right] * \left[ 1 - h_{ij}^{oc} \right] \right\} \quad (4.15)$$

$$S_{ij} = S_{ij}^{fc} * S_{ij}^{oc} \quad (4.16)$$

There are three types of contribution to the likelihood: that for an individual exiting to fixed-contracts ($L^{fc}$), that for an individual exiting to open-ended contracts ($L^{oc}$), and that for a censored ($L^{c}$):

$$L^{c} = S_{ij} = S_{ij}^{fc} * S_{ij}^{oc}$$

$$L^{ft} = \Pr(t_{j-1} < T_{fc} \le t_j, T_{oc} > T_{ft}) = \int_{t_j - 1}^{t_j} \left[ \int_{u}^{t_j} f_{ft}(u) f_{oc}(v) dv + \int_{t_j}^{\infty} f_{ft}(u) f_{oc}(v) dv \right] du$$

$$L^{oc} = \Pr(t_{j-1} < T_{oc} \le t_j, T_{fc} > T_{oc}) = \int_{t_j - 1}^{t_j} \left[ \int_{u}^{t_j} f_{ft}(u) f_{oc}(v) dv + \int_{t_j}^{\infty} f_{ft}(u) f_{oc}(v) dv \right] du \quad (4.17)$$

where $T_{oc}$, $T_{ft}$ and $f_{ft}$, $f_{oc}$ are the destination-specific latent failure times and density functions respectively. The lower integration point in the second integral, u, is the (unobserved) time within the interval at which the exit to fc/oc occurred. To proceed further, I make the assumption that transitions can only occur at the boundaries of the intervals[14]. Then the overall likelihood contribution for the person with a spell length $t_j$ is given by:

$$L_{ij} = \left(L_{ij}^{fc}\right)^{\delta_{fc}} \left(L_{ij}^{oc}\right)^{\delta_{oc}} \left(L_{ij}\right)^{1-\delta_{fc}-\delta_{oc}}$$

$$= \left[ \frac{h_{ij}^{fc}}{1 - h_{ij}^{fc}} \right]^{\delta_{fc}} S_{ij}^{fc} \left[ \frac{h_{ij}^{oc}}{1 - h_{ij}^{oc}} \right]^{\delta_{oc}} S_{ij}^{oc} \quad (4.18)$$

where $\delta_{fc}$ and $\delta_{oc}$ are the destination-specific censoring indicators. Thus the likelihood contribution partitions into a product of terms, each of which is a function of a single destination-specific hazard only. Consequently, it is possible to estimate the overall independent competing risk model by estimating separate destination-specific models having defined suitable destination-specific censoring variables.

[14] The assumption may not be an appropriate one in practice. So I have also estimated a multinomial logit model, originally developed for intrinsically discrete data. If the interval hazard rate was relatively small, this model may provide estimates that are a close approximation to a model for grouped-data with the assumption that the (continuous) hazard is constant within intervals.

As in the previous models, also in the competing risks one I have accommodated the presence of observed individual heterogeneity assuming a multiplicative error term associated with each specific hazard function (Mixed Independent Competing Risk Model, MICR) . I further assume that the errors are gamma distributed with mean 1 and variance $\sigma^2$.

## 5. Estimation results and discussion

In this section discussion of results from estimation will be made. The first set of results in this study is that which is based on non-parametric duration analysis, the second set is from single risk duration models with and without unobserved heterogeneity (PH and MPH). Finally the third set of results is from independent competing risk models with unobserved heterogeneity (MICR).

### 5.1 Non-parametric duration analysis

In the non-parametric approach to the duration analysis I provide the estimates of the Life-table's survivor and hazard functions in Table 1. They are the generalization of the Kaplan-Meier survivor and hazard functions for interval-censored data. Figure 1 and 2 give the plots of the aggregate and disaggregated (by subject groups) Life-table's survivor functions. The survivor function shows the proportion of people who survive unemployment as time proceeds. The graph imply that graduates in Humanities have the longest unemployment durations, followed by graduates in Social Sciences. The survivor functions for graduates in Engineering and in Scientific subjects decline more steeply than graduates from other groups implying that graduates in Engineering/Scientific subjects find jobs sooner than graduates in other subjects. The figure also implies that for graduates in Humanities, Social sciences, Scientific subjects and Engineering the probabilities of surviving beyond 10 quarters are respectively: 0.40, 0.33, 0.28, 0,21.
Figure 3 and 4 provide the plots of the aggregate and disaggregated hazard functions. As we can see from the graph for all data, the hazard rate increases over the quarters. If we look at the results for different subject groups, we observe that the hazard for graduates in engineering is larger than that for graduates in other groups until about the 15$^{th}$ quarter.
The log-rank and the Wilcoxon tests allow for testing for the equality of two or more survivor functions. Table 1 gives the log-rank and Wilcoxon tests results for course-program grouping. We

observe from the table that the null hypothesis of equality of survivor functions for different groups is rejected by both tests.

**5.2 Results from Proportional Hazard models**

I will discuss and report only the estimation results from the complementary log-log model, because the proportional odds model provides almost equal estimates[15].

The PH is estimated with two types of specification for the baseline hazard: the log-polynomial and the piecewise constant exponential. The log-polynomial specification imposes a particular shape for baseline hazard while the piecewise constant exponential provides a more flexible specification and have an additional advantage in that parameters estimates are less sensitive to the distributional assumptions made for unobserved heterogeneity. Both homogeneous and mixing proportional hazards have been estimated. The mixing models estimated assumes that the distribution of the unobserved heterogeneity is either normal or gamma or discrete. In the log-polynomial specification without unobserved heterogeneity the estimated coefficients of ln(t), t^2 and t^3 reveal that the baseline hazard decreases to a single minimum and then increases towards infinite thereafter: a period of negative duration dependence is followed by positive duration dependence. The same coefficients in the specifications with gamma unobserved heterogeneity are smaller in absolute value terms, indicating a more marked positive dependence. Likelihood ratio test of zero gamma unobserved heterogeneity is also rejected decisively underlying the importance of accounting for unobserved heterogeneity. In the discrete distribution the coefficient of ln(t) is positive, indicating only positive duration dependence.. If we suppose that the frailty term is normally distributed the coefficients of duration dependence and of the covariates equal those of the no-frailty model but in this case the likelihood ratio test suggests statistically not significant frailty: the assumption that the unobserved heterogeneity is normally distributed is probably incorrect . In the piecewise constant exponential specification, baseline hazard estimates under the assumption of gamma and discrete mixing distribution are higher than those obtained under the assumption of homogeneous and normal mixing distributions. The patterns of the baseline hazard functions are shown in figure 6 where we can see that although there are some differences in the magnitude of the estimated hazards from the different models, all the different baseline hazards increase with time, after a short period of negative duration dependence. But accounting for unobserved heterogeneity does increase the observed positive duration dependence. As such,

[15] The 2 models provide similar estimates if the hazard is small. If $h \rightarrow 0$, the proportional odds model (logit(h)=log(h/1-h)=log(h)-log(1-h)), becomes a proportional hazard model.

therefore, these results are in line with the common claim in the literature that accounting for unobserved heterogeneity increases positive duration dependence.

Results showing the estimated effects of covariates on the hazard of employment are given in Table 2 for the log-polynomial specification (with and without unobserved heterogeneity) and in Table 3 for the piecewise constant exponential none (with and without unobserved heterogeneity).

As can be seen from the estimation results of the log-polynomial specification in Table 2, the estimated coefficients under the assumption of gamma mixing distribution are slightly larger in absolute value terms with respect to those under the assumption of homogeneous and discrete mixing distribution. Starting with the effect of personal characteristics on the hazard of exit out of unemployment, older graduates are found to have a lower hazard of employment compared with their younger counterparts: a one year rise in age is associated with a 7% (9%, 8%) lower hazard rate in the homogeneous (gamma, discrete) model. So younger graduates find their first job earlier. This could be explained by the fact that younger students are more likely to be better students because they might have received their degree in the institutional time established for the course programme they attended. These findings are in line with mine expectations. With regard to gender differences, female graduates have a 13% (26%, 9%) lower hazard of employment compared with male graduates in the homogeneous (gamma, discrete) model. An explanation for this that best fits the labour economics literature is, of course, that men are generally expected to receive more job offers than women do, mainly due to the female labour market behaviour that is (or perceived to be) characterized by frequent interruptions.

Males who did their service after their degree have a 37% (69%, 15%) lower hazard of employment with respect to males who did it before their degree or were exempted from military service in the homogeneous (gamma, discrete) model. Actually, the starting date of military service is unknown, but this lack of information is not a serious problem here since military service was 1 year long, with the possible call occurring within 1 year after graduation; hence a military service covariate equal to 1 indicates that the service started and ended within the observation period of the survey, thus controlling for a definitely prior event. Graduates who transferred in another region to attend university have a 6% (10%) higher hazard of finding their first job in the homogeneous (discrete) model[16]. This could be explained by the fact that individuals who moved in another region to study may be more motivated and better students than those who didn't experience any transfer.

Considering the covariate related to academic ability, the final mark has not a statistically significant effect on the probability of obtaining the first job. The low influence of the final mark

[16] This is not true if we consider the gamma model, where the variable mobility is not statistically significant.

might be explained by the previously mentioned ceiling effect. The mark and type of high school seem not to exert any impact on the hazard of employment.

Graduates who were employed in the labour market while studying have a 11% (24%) lower hazard of exit from unemployment in the homogeneous (gamma) model: this is not in line with the a-priori that employers prefer individuals with some work experience, though seasonal or occasional.

There are significant differences in graduates' hazard of employment according to subject studied at university, even using the highly aggregated set of 4 broad subject areas. Relative to students of Scientific subjects, Engineering students have a 14% (27%, 12%) higher hazard rate of getting the first job in the homogeneous (gamma, discrete) model. The equivalent hazards for Social sciences and Humanities students are respectively 15% (24%, 13%) and 30% (47%, 28%) lower.

As regards the graduates' social background, educational level of the parents at the date of degree seems to have only a slightly positive effect on the probability of obtaining the first job. Thus for example graduates with at least one parent with a high school degree have higher hazard of employment with respect to graduates with parents having the lowest level of education (illiteracy or primary school). The other levels of education have not a significant effect on the hazard. On the other hand, the father's occupation seem to be more important for graduates' chances of employment: those with a father entrepreneur, manager or white collar high level have higher hazard rates with respect to those with a father employed in non-qualified occupations.

Finally the estimated results suggest strong regional variation in the patterns of exit from unemployment. Those individuals who attended university in southern and central Italy have longer duration of unemployment compared with their counterparts in the north of the country. In particular, in the homogeneous (gamma, discrete) model those who took their degree in the centre and south of the country have a 23% (36%, 18%) and 40% (64%, 31%) lower hazard rate of employment compared with their counterparts in the North of Italy. Since there is a strong correlation between region of university attended and region of actual residence, the geographical variables used here serve as proxy for local labour market conditions that are usually captured using local unemployment and vacancy rates.

Results showing the estimated coefficients of the piecewise model are discussed below. The effects of covariates on the hazard of exit from unemployment are more or less similar across the three models estimated, with only marginal differences. This supports Meyer's (1990) suggestion that using a flexible specification for the baseline hazard removes the sensitivity of estimated parameters to the type of distribution assumed for unobserved heterogeneity. Comparing the maximum of the log-likelihoods from the piecewise constant models shows that the gamma and discrete model have an edge over the other two models. As a result, I will discuss the covariate effects on the hazard relying on the gamma and discrete model.

Male graduates who did their service after their degree have a 40% (18%) lower hazard of employment with respect to males who did it before their degree or were exempted from military service in the gamma (discrete) model. Older graduates are found to have a lower hazard of employment compared with their younger counterparts. Women who are unemployed after graduation have a 15% (7%) lower hazard of employment compared with their men counterparts. Graduates who transferred in another region to attend university have a 6% (10%) higher hazard of finding their first job in the homogeneous (discrete) model. As before, final mark at university and high school have not a statistically significant effect on the hazard. Graduates who were employed in the labour market while studying have a 9%(2%) lower hazard of exit from unemployment in the gamma (discrete) model. Engineering graduates perform better in terms of unemployment duration than graduates in Scientific subjects: the hazard of exit from unemployment of the former is in fact 14% (8%) higher. The Social sciences and Humanities students have instead longer duration of unemployment. As in the previous model, social background seems to exert an effect on the hazard of employment only through father's occupation: graduates with a father entrepreneur, manager or white collar high level have more or less a 15% higher hazard of employment compared with those with a father employed in non-qualified occupations. In terms of regions, those who attended university in the central and Southern Italy tend to have longer unemployment duration compared with their counterparts in the North of the country: Southern Italian graduates, for example, have a 42% (30%) lower hazard of finding the first job in the gamma (discrete).

### 5.3 Results Independent Competing Risks Models

I now consider the issue of destination state. Sample means of jobless duration and of number of exits are given in Table 4. Comparing individuals entering in to fixed-term contracts with individuals entering in to open-ended employment, it can be seen that their elapsed unemployment duration is much longer. However, the most common form of transition is to open-ended contracts rather than fixed-term employment.

The disaggregated version of the piecewise constant hazard regressions (under the assumption that exits can occur at interval boundaries) are given in Table 4. The estimates correct for unobserved heterogeneity[17], assuming a gamma mixing distribution. It is immediately apparent that the regression coefficients vary widely from destination state to destination state. Thus, for example, the probability of finding employment in open-ended contracts is increasing with the level of education of parents. But these effects of parental education are confined to open-ended contracts. This is also true if we consider father's occupation: having a father either entrepreneur or manager or professional worker or white collar high level increases the hazard rate of open-ended employment but not of fixed term contract. Female graduates have a higher hazard of exit to fixed term contracts but a lower hazard of exit to open-ended employment compared to their male counterparts. These findings caution against uncritical aggregation by destination state. Another interesting result is that graduation in Engineering is associated with a sharply reduced likelihood of entering into fixed-term contracts. The same is true for graduates in Social sciences. The probability of escaping in to permanent jobs is negatively associated with graduation in Humanities. Mobility increases only the probability of fixed term employment. Those who took their degree in the Centre of Italy are less likely to enter open-ended employment than their Northern Italian counterparts, this is not true if we consider exit to fixed-term contract. Southern graduates are less likely to exit to both states, though this effect is more pronounced if we consider exit to open-unemployment contract. Males who did their service after their degree are more penalized in terms of probability of entering open-ended contracts: their hazard of exit into this state is 46% lower compared to males who did it before their degree or were exempted from military service. The hazard of exit to fixed term contracts instead is only 8% lower. As in the previous models, age and work experience while at university have a negative effect on the hazard of exit from unemployment. The final mark at university and high school are not statistically significant. Very similar results are obtained estimating a multinomial logit model, under the assumptions that the interval-hazard is small and that the continuous hazard is constant within intervals.

Baseline hazard functions, corresponding to the piecewise constant exponential specification, are given in Figure 7. These results are obtained by setting all covariate values equal to zero. It is apparent that the baseline hazards are both characterized by declining escape rates over the first quarter, later there is evidence of positive duration dependence. Indeed, open-ended employment is generally characterized by higher hazard rates with respect to those of fixed-contracts state. However in the final quarters there is a sharp increase of hazard of exit to fixed-term contracts. Taken in conjunction the two baseline hazards perhaps suggest that some graduates initially looking for open-ended employment switch to sampling fixed-term contracts after a period of unsuccessful search.

[17] It is important to stress that in these models unobserved heterogeneity is not so important as in the previous one: the likelihood ratio test of zero unobserved heterogeneity for the gamma distribution is weakly rejected.

## 6. Conclusion

This paper attempted to analyse the duration of unemployment for Italian graduates. The focus of the study has been on the time to obtain the first job, taking into account the graduates' characteristics and the effects relating to course programmes. Parametric and non-parametric discrete-time models have been used to study the hazard of exit to first job. Alternative mixing distributions have also been employed to account for unobserved heterogeneity. The results obtained indicate that there is evidence of positive duration dependence after a short initial period of negative duration dependence. Accounting for unobserved heterogeneity does matter, but the main finding to duration dependence remains unchanged. With regards to the effects of covariates, older and female graduates, those who graduated in Humanities and Social sciences, those who had fathers employed in non-qualified occupations , those males who did their service after their degree and finally those who attended university in southern and central Italy are found to have particularly lower hazard of getting their first job.

In addition, competing risk model with unobserved heterogeneity and semi-parametric baseline hazard have been estimated to characterize transitions out of unemployment, accommodating behaviourally distinct choices on the part of job seekers. Mine results reveal that the use of an aggregate approach sometimes compound distinct and contradictory effects. Thus, for example, the probability of finding employment in open-ended contracts is increasing with the level of education of parents. But these effects are completely absent if we consider exit to fixed-term contracts. Female graduates have a higher hazard of exit to fixed contracts but a lower hazard of exit to open-ended employment compared to their male counterparts. Those who took their degree in the Centre of Italy are less likely to enter open-ended employment than their Northern Italian counterparts, this is not true if we consider exit to fixed term contract. Very similar results are obtained estimating a multinomial logit model.

**References**


Allison, P. D. (1982), “Discrete-time methods for the analysis of event histories” Sociological Methodology, 13, 61-98.

Biggeri L., Bini M. and Grilli L. (2000), “The transition from university to work: a multilevel approach to the analysis of the time to obtain the first job”, J. R. Statistical Society A, 164, 293-305.

Boero G., McKnight A., Naylor R. and Smith J. (2001), “Graduates and Graduate Labour markets in the UK and in Italy”, Crenos, Contributi di Ricerca 01/11.

Cox, D. R. (1972), “Regression models and life-tables” (with discussion), J. R. Statistical Society B, 34, 187-220.

Censis, “Rapporto sulla situazione del Paese, anno 1998”.

Devine, T.J. and N.M. Kiefer (1991), “Empirical Labor Economics”, Oxford University Press: Oxford.

Dolton, P. J., Makepeace, G. H. and Treble, J. G. (1994) “The youth training scheme and the school to work transition”, Oxford Economic Papers, 46,4, 629-657.

Eckstein, Z. and Van den Berg, (2003), “ Empirical Labor Search: A Survey”, IZA Discussion Paper No. 929.

Firth, D. et al (1999), “Efficacy of programmes for the unemployed: discrete time modelling of duration data from a matched comparison study. J. R. Statistic. Soc. A, 162, 111-120.

Han, A. and J. Hausman (1990), “Flexible Parametric Estimation of Duration and Competing Risk Models”, Journal of Applied Econometrics, 5(1), 1-28.

Heckman, J. and B. Singer (1984a) “The identifiability of The Proportional Hazard Model”, Review of Economic Studies, LI, 231-241.

Heckman, J. and B. Singer (1984b) “ A Method for Minimizing the Impact of Distributional Assumptions in Econometric Models for Duration Data”, Econometrica, 52(2), 271-320.
ISTAT, “Rilevazione delle forze di lavoro, anno 1999”.

ISTAT, “Rapporto annuale, 1998”.

Jenkins, S. P. (1995), “Easy Estimation Methods for Discrete-Time Duration Models” Oxford Bulletin of Economics and Statistics, 57(1), 129-138.

Jenkins, S. P. (1997), “sbe17: Estimation Methods for Discrete-Time (Grouped Duration Data) Proportional Hazard Models: PGMHAZ”, Stata Technical Bulletin, 39, 1-12.

Jenkins, S. P. (2004) “Survival Analysis”, mimeo, Department of Economics, University of Essex, UK.

Kiefer N. (1988) “Economic Duration Date and Hazard Functions”, Journal of economic Literature, XXVI, 646-679.

Lancaster T. (1979), “Econometric Methods of the Duration of Unemployment” Econometrica, 47(4), 939-956.

Lancaster, T. (1990), “The Econometric Analysis of Transition Data”, Econometric Society Monographs, Cambridge University Press, Cambridge.

Layder, D. et al. (1991), “ The empirical correlates of action and structure: the transition from school to work”, Sociology, 25, 447-464.

Lynch, L. M. (1987), “Individual differences in the youth labour market: a cross-section analysis of London youths”, From School to Unemployment?: the Labour Market for Young People, pp.185-211. London: Macmillan.

Mealli, F. and Pudney S. (1999), “Specfication tests for random effects transition models: an application to a model of the role of YTS in the youth labour market”. Lifetime Data Anal. 5, 213-237.

Meyer, B. D. (1990), "Unemployment Insurance and Unemployment Spells" Econometrica 58: 757-782.

Narendranathan, W. and Stewart B. M. (1993a), "How Does the Unemployment Effect Vary as Unemployment Spell Lenghtens?", Journal of Applied Econometrics 8: 361-381.

Narendranathan, W. and Stewart B. M., 1993b "Modelling the Probability of Leaving Unemployment: Competing Risks Models with Flexible Base-line Hazards", Applied Statistics 42: 63-83.

Neumann, G. (1990), "Search Models and Duration Data", Handbook of Applied Ecnometrics, Chapter 4.

OCSE, Regard sur l'education, 1997.

Portugal P. and Addison J. (2003), "Six Ways to Leave Unemployment", IZA Discussion Paper No 954.

Rogerson, R. and R. Wright (2001), "Search-theoretical models of the labor market", Working Paper, University of  Pennsylvania, Philadelphia.

Santoro, M. and Pisati, M. (1996), "Dopo la laurea" Bologna: Il Mulino.

Tronti, L. and Mariani, P. (1994), "La transizione Università-Lavoro in Italia: un'esplorazione delle evidenze dell'indagine ISTAT sugli sbocchi professionali dei laureati", Econ. Lav., 25, no. 3, 3-26.

Van den Berg, G. (1990), "Nonstationary in Job Search Theory", Review of Economic Studies, 57, 255-277.

Van den Berg, G. (2001), "Duration Models: Specification, Identification and Multiple Durations", in Handbook of Econometrics, edited by Heckman, James J. and Leamer Edward, V, North-Holland, Amsterdam.

Wolpin, K. (1987), “Estimating a Structural Search Model: The Transition from School to Work”, Econometrica, 55, 801-817.

**Figure 1: Empirical Survivor Function.**

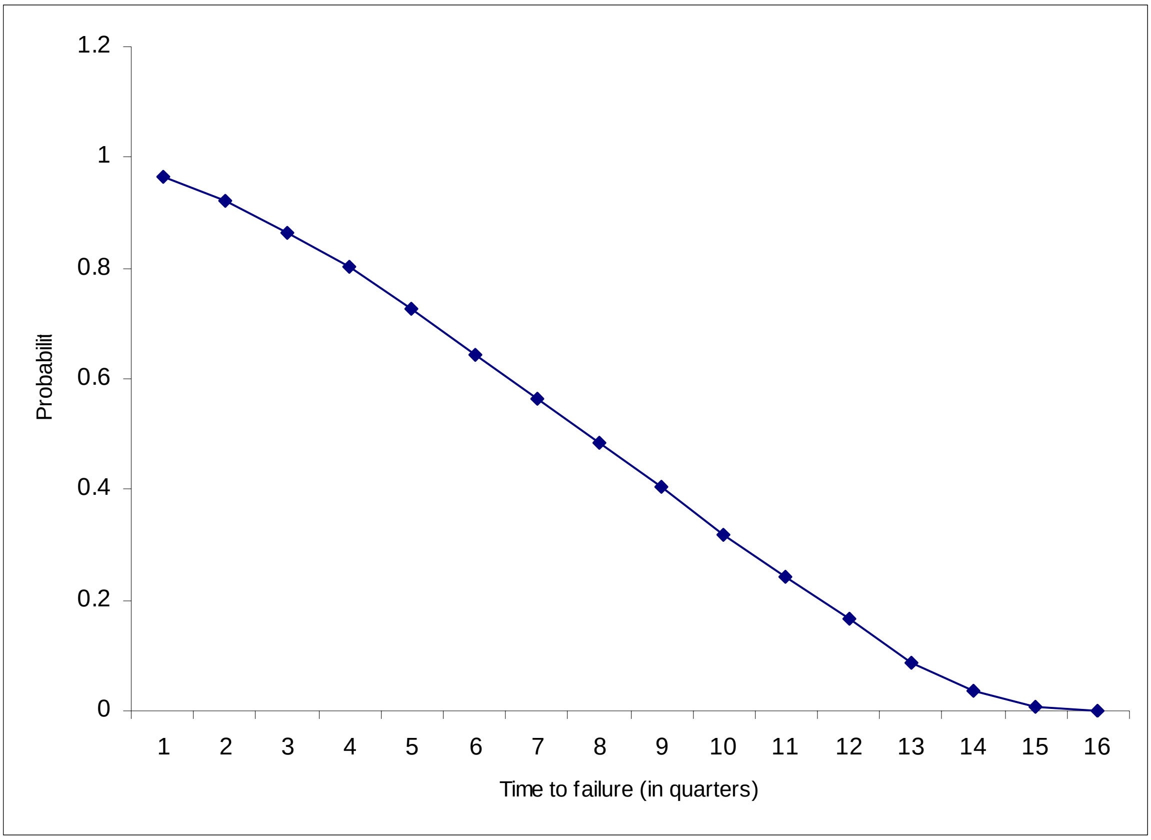



**Figure 2: Empirical Survivor Function by University Group.**

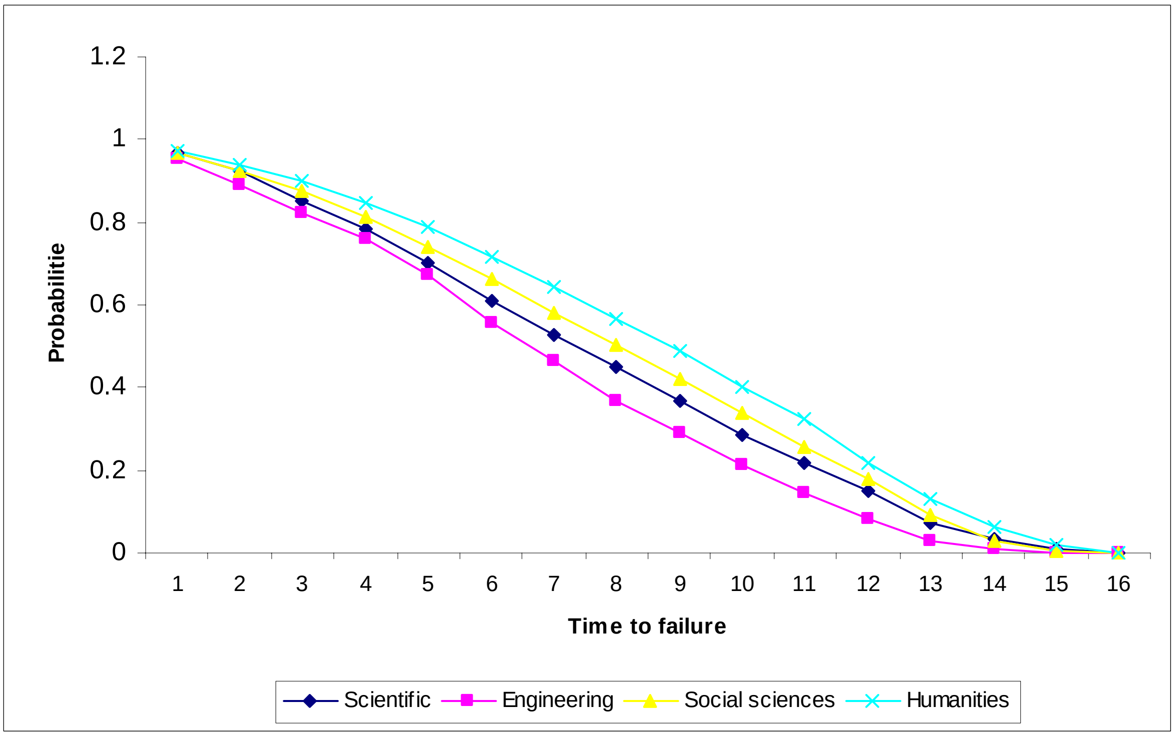


**Figure 3: Empirical Hazard Function.**

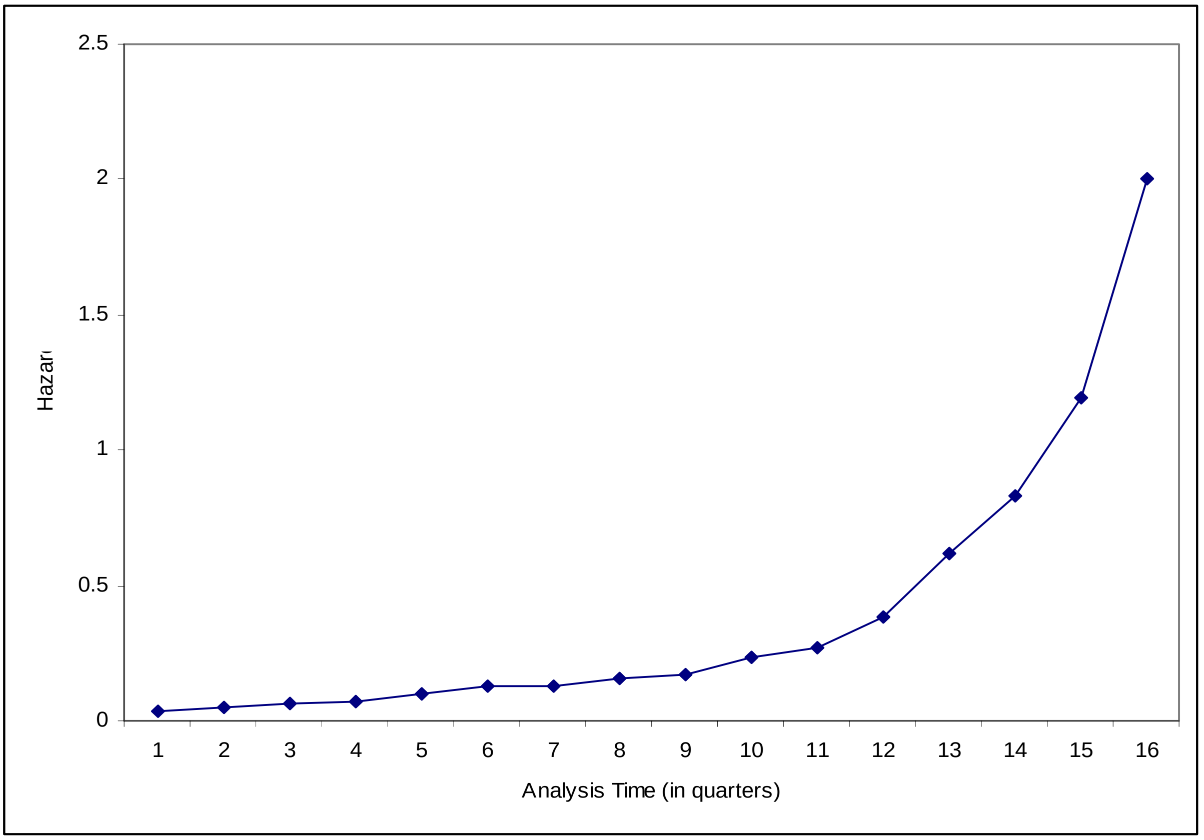



**Figure 4: Empirical Hazard Functions by University group.**

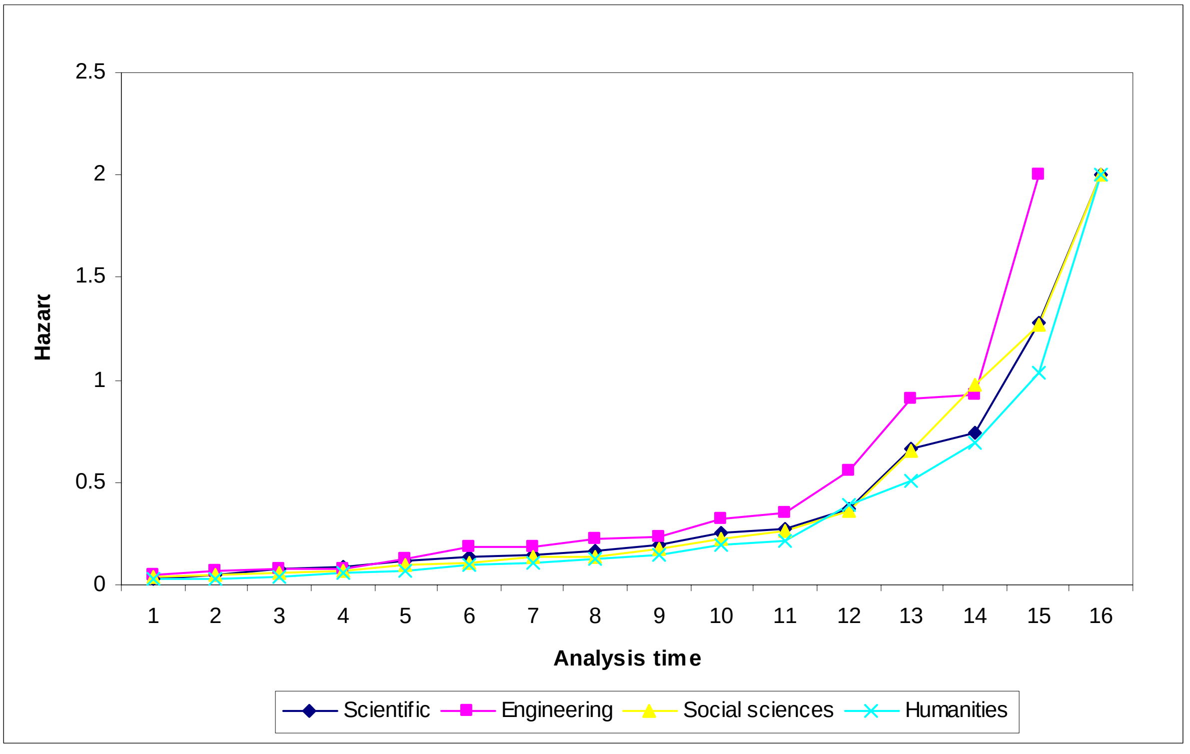


**Figure 5: Baseline Hazard Functions  in the log-polynomial specification under different distributions for unobserved heterogeneity.**

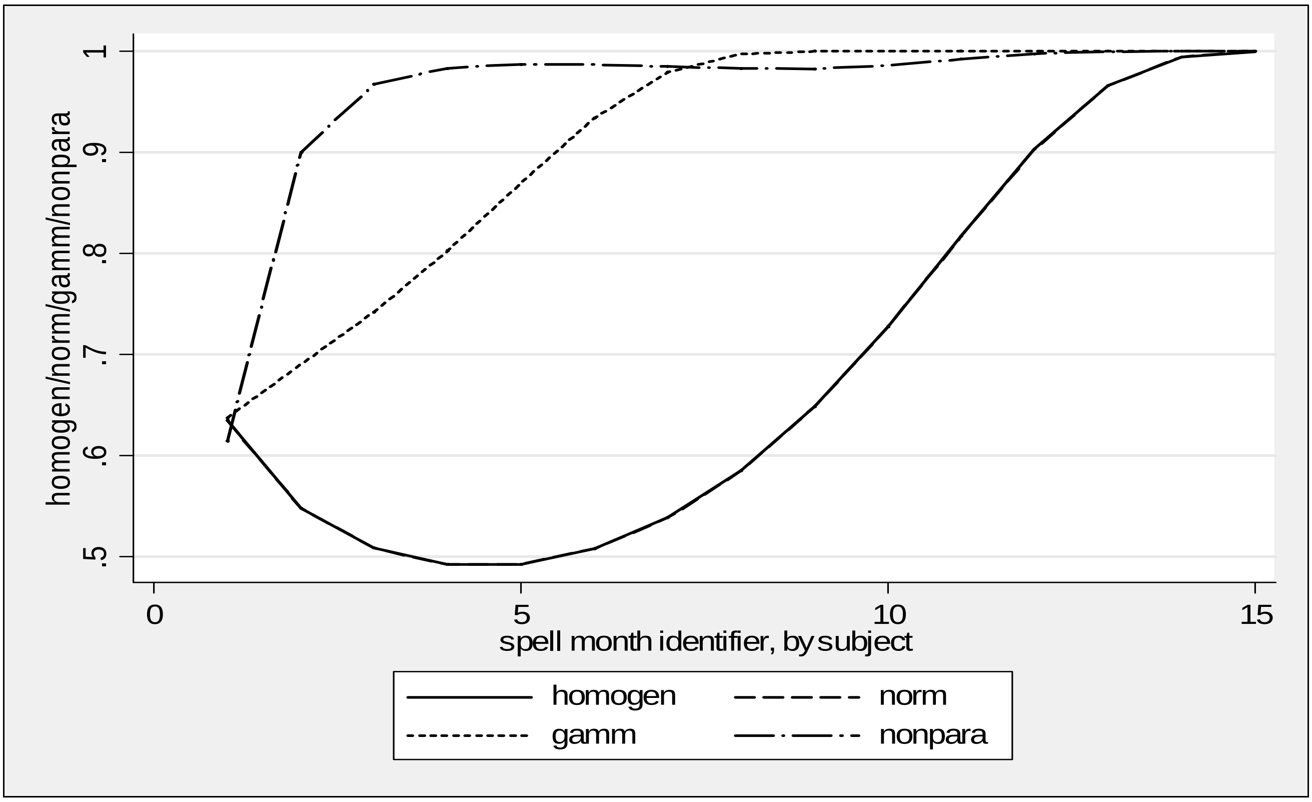



**Figure 6: Baseline Hazard Functions  in the piecewise constant specification under different distributions for unobserved heterogeneity.**

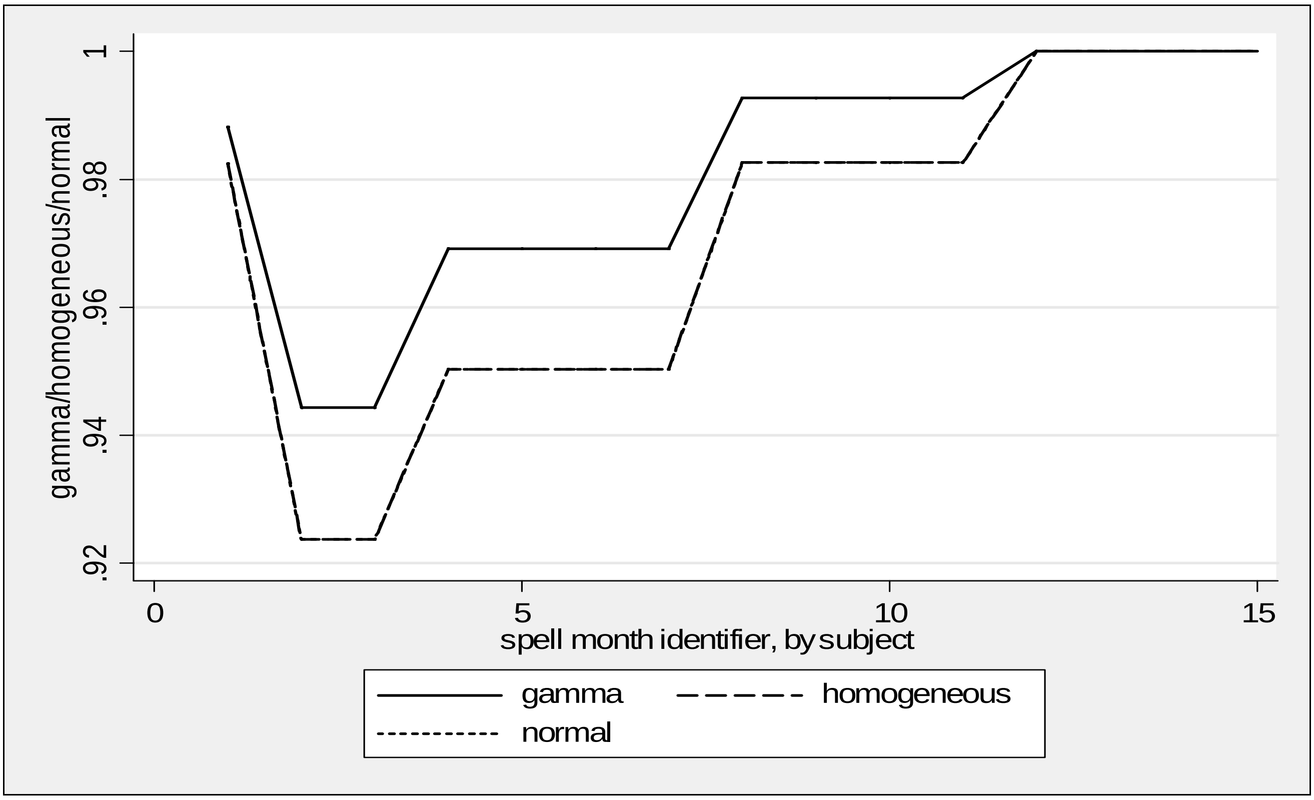
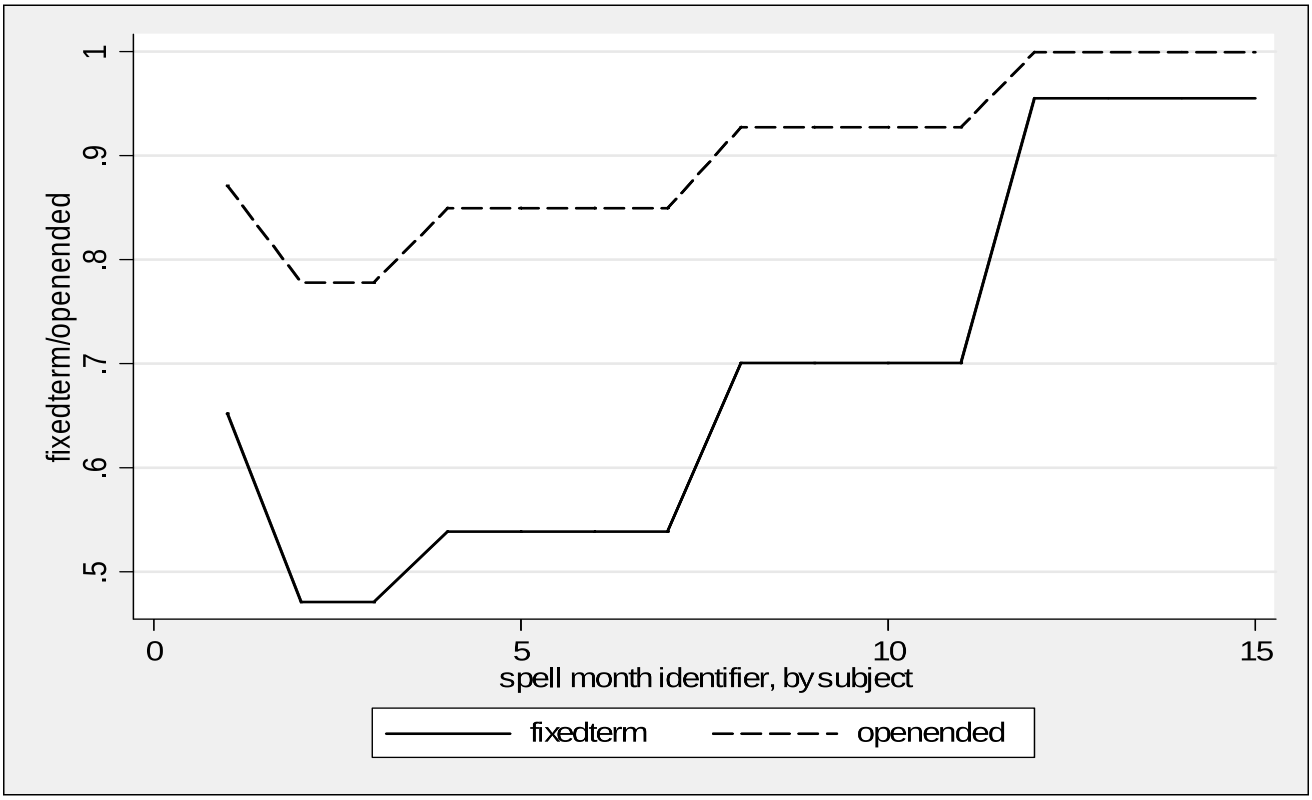


**Figure 7: Baseline Hazard Functions by Destination State.**



## Table 1: Empirical Hazard and Survivor Function.

| Group | Intervals | | Total | Deaths | Survival | se Survival | Hazard | Se Hazard | Hazard | Se hazard |
|---|---|---|---|---|---|---|---|---|---|---|
| **Scientific** | 0 | 1 | 9922 | 302 | 0.9696 | 0.0017 | 0.966 | 0.9728 | 0.0309 | 0.0018 |
| | 1 | 2 | 9620 | 458 | 0.9234 | 0.0027 | 0.918 | 0.9285 | 0.0488 | 0.0023 |
| | 2 | 3 | 9162 | 712 | 0.8516 | 0.0036 | 0.8445 | 0.8585 | 0.0809 | 0.003 |
| | 3 | 4 | 8450 | 678 | 0.7833 | 0.0041 | 0.7751 | 0.7913 | 0.0836 | 0.0032 |
| | 4 | 5 | 7772 | 828 | 0.6999 | 0.0046 | 0.6907 | 0.7088 | 0.1125 | 0.0039 |
| | 5 | 6 | 6944 | 895 | 0.6097 | 0.0049 | 0.6 | 0.6192 | 0.1378 | 0.0046 |
| | 6 | 7 | 6049 | 804 | 0.5286 | 0.005 | 0.5187 | 0.5384 | 0.1424 | 0.005 |
| | 7 | 8 | 5245 | 798 | 0.4482 | 0.005 | 0.4384 | 0.458 | 0.1647 | 0.0058 |
| | 8 | 9 | 4447 | 800 | 0.3676 | 0.0048 | 0.3581 | 0.3771 | 0.1977 | 0.007 |
| | 9 | 10 | 3647 | 810 | 0.2859 | 0.0045 | 0.2771 | 0.2948 | 0.2498 | 0.0087 |
| | 10 | 11 | 2837 | 690 | 0.2164 | 0.0041 | 0.2083 | 0.2245 | 0.2769 | 0.0104 |
| | 11 | 12 | 2147 | 671 | 0.1488 | 0.0036 | 0.1418 | 0.1558 | 0.3704 | 0.0141 |
| | 12 | 13 | 1476 | 732 | 0.075 | 0.0026 | 0.0699 | 0.0803 | 0.6595 | 0.023 |
| | 13 | 14 | 744 | 403 | 0.0344 | 0.0018 | 0.0309 | 0.0381 | 0.7429 | 0.0344 |
| | 14 | 15 | 341 | 266 | 0.0076 | 0.0009 | 0.006 | 0.0094 | 1.2788 | 0.0603 |
| | 15 | 16 | 75 | 75 | 0 | . | . | . | 2 | 0 |
| **Engineering** | 0 | 1 | 8555 | 400 | 0.9532 | 0.0023 | 0.9486 | 0.9575 | 0.0479 | 0.0024 |
| | 1 | 2 | 8155 | 539 | 0.8902 | 0.0034 | 0.8834 | 0.8967 | 0.0684 | 0.0029 |
| | 2 | 3 | 7616 | 596 | 0.8206 | 0.0041 | 0.8123 | 0.8285 | 0.0814 | 0.0033 |
| | 3 | 4 | 7020 | 504 | 0.7617 | 0.0046 | 0.7525 | 0.7705 | 0.0745 | 0.0033 |
| | 4 | 5 | 6516 | 768 | 0.6719 | 0.0051 | 0.6618 | 0.6817 | 0.1252 | 0.0045 |
| | 5 | 6 | 5748 | 990 | 0.5562 | 0.0054 | 0.5456 | 0.5666 | 0.1885 | 0.006 |
| | 6 | 7 | 4758 | 804 | 0.4622 | 0.0054 | 0.4516 | 0.4727 | 0.1846 | 0.0065 |
| | 7 | 8 | 3954 | 805 | 0.3681 | 0.0052 | 0.3579 | 0.3783 | 0.2267 | 0.0079 |
| | 8 | 9 | 3149 | 664 | 0.2905 | 0.0049 | 0.2809 | 0.3001 | 0.2357 | 0.0091 |
| | 9 | 10 | 2485 | 684 | 0.2105 | 0.0044 | 0.2019 | 0.2192 | 0.3192 | 0.012 |
| | 10 | 11 | 1801 | 540 | 0.1474 | 0.0038 | 0.14 | 0.155 | 0.3527 | 0.0149 |
| | 11 | 12 | 1261 | 550 | 0.0831 | 0.003 | 0.0774 | 0.0891 | 0.5578 | 0.0228 |
| | 12 | 13 | 711 | 444 | 0.0312 | 0.0019 | 0.0277 | 0.0351 | 0.908 | 0.0384 |
| | 13 | 14 | 267 | 169 | 0.0115 | 0.0012 | 0.0094 | 0.0139 | 0.926 | 0.0631 |
| | 14 | 15 | 98 | 98 | 0 | . | . | . | 2 | 0 |
| **Social sciences** | 0 | 1 | 14964 | 508 | 0.9661 | 0.0015 | 0.963 | 0.9688 | 0.0345 | 0.0015 |
| | 1 | 2 | 14456 | 625 | 0.9243 | 0.0022 | 0.9199 | 0.9284 | 0.0442 | 0.0018 |
| | 2 | 3 | 13831 | 736 | 0.8751 | 0.0027 | 0.8697 | 0.8803 | 0.0547 | 0.002 |
| | 3 | 4 | 13095 | 900 | 0.815 | 0.0032 | 0.8086 | 0.8211 | 0.0712 | 0.0024 |
| | 4 | 5 | 12195 | 1132 | 0.7393 | 0.0036 | 0.7322 | 0.7463 | 0.0973 | 0.0029 |
| | 5 | 6 | 11063 | 1155 | 0.6621 | 0.0039 | 0.6545 | 0.6696 | 0.1102 | 0.0032 |
| | 6 | 7 | 9908 | 1230 | 0.5799 | 0.004 | 0.572 | 0.5878 | 0.1324 | 0.0038 |
| | 7 | 8 | 8678 | 1141 | 0.5037 | 0.0041 | 0.4956 | 0.5117 | 0.1407 | 0.0042 |
| | 8 | 9 | 7537 | 1208 | 0.4229 | 0.004 | 0.415 | 0.4309 | 0.1742 | 0.005 |
| | 9 | 10 | 6329 | 1296 | 0.3363 | 0.0039 | 0.3288 | 0.3439 | 0.2281 | 0.0063 |
| | 10 | 11 | 5033 | 1170 | 0.2582 | 0.0036 | 0.2512 | 0.2652 | 0.263 | 0.0076 |
| | 11 | 12 | 3863 | 1177 | 0.1795 | 0.0031 | 0.1734 | 0.1857 | 0.3594 | 0.0103 |
| | 12 | 13 | 2686 | 1320 | 0.0913 | 0.0024 | 0.0867 | 0.096 | 0.6515 | 0.017 |
| | 13 | 14 | 1366 | 897 | 0.0313 | 0.0014 | 0.0286 | 0.0342 | 0.9777 | 0.0285 |
| | 14 | 15 | 469 | 364 | 0.007 | 0.0007 | 0.0058 | 0.0085 | 1.2683 | 0.0514 |
| | 15 | 16 | 105 | 105 | 0 | . | . | . | 2 | 0 |

## Table 1: Empirical Hazard and Survivor Function (continuing).

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| **Humanities** | 0 | 1 | 9709 | 286 | 0.9705 | 0.0017 | 0.967 | 0.9737 | 0.0299 | 0.0018 |
| | 1 | 2 | 9423 | 295 | 0.9402 | 0.0024 | 0.9353 | 0.9447 | 0.0318 | 0.0019 |
| | 2 | 3 | 9128 | 382 | 0.9008 | 0.003 | 0.8947 | 0.9066 | 0.0427 | 0.0022 |
| | 3 | 4 | 8746 | 516 | 0.8477 | 0.0036 | 0.8404 | 0.8547 | 0.0608 | 0.0027 |
| | 4 | 5 | 8230 | 576 | 0.7883 | 0.0041 | 0.7801 | 0.7963 | 0.0725 | 0.003 |
| | 5 | 6 | 7654 | 705 | 0.7157 | 0.0046 | 0.7066 | 0.7246 | 0.0966 | 0.0036 |
| | 6 | 7 | 6949 | 690 | 0.6447 | 0.0049 | 0.635 | 0.6541 | 0.1045 | 0.004 |
| | 7 | 8 | 6259 | 749 | 0.5675 | 0.005 | 0.5576 | 0.5773 | 0.1273 | 0.0046 |
| | 8 | 9 | 5510 | 760 | 0.4892 | 0.0051 | 0.4793 | 0.4991 | 0.1481 | 0.0054 |
| | 9 | 10 | 4750 | 837 | 0.403 | 0.005 | 0.3933 | 0.4128 | 0.1932 | 0.0066 |
| | 10 | 11 | 3913 | 750 | 0.3258 | 0.0048 | 0.3165 | 0.3351 | 0.212 | 0.0077 |
| | 11 | 12 | 3163 | 1034 | 0.2193 | 0.0042 | 0.2111 | 0.2276 | 0.3908 | 0.0119 |
| | 12 | 13 | 2129 | 864 | 0.1303 | 0.0034 | 0.1237 | 0.1371 | 0.5091 | 0.0168 |
| | 13 | 14 | 1265 | 650 | 0.0633 | 0.0025 | 0.0586 | 0.0683 | 0.6915 | 0.0254 |
| | 14 | 15 | 615 | 420 | 0.0201 | 0.0014 | 0.0174 | 0.023 | 1.037 | 0.0433 |
| | 15 | 16 | 195 | 195 | 0 | . | . | . | 2 | 0 |

## Table 1.2: Log-rank and Wilcoxon (Breslow) tests.

| **Log-rank test for equality of survivor functions** | **Events observed** | **Events expected** | |
|---|---|---|---|
| **Scientific** | 2412 | 2297.88 | |
| **Engineering** | 2364 | 1929.52 | |
| **Social sciences** | 3414 | 3565.97 | |
| **Humanities** | 1973 | 2369.62 | |
| **Total** | 10163 | 10163 | |
| | chi2(4) = | 235.88 | |
| | Pr>chi2 = | 0 | |
| **Wilcoxon (Breslow) test** | **Events observed** | **Events expected** | **Sum of ranks** |
| **Scientific** | 2412 | 2297.88 | 487960 |
| **Engineering** | 2364 | 1929.52 | 3361126 |
| **Social sciences** | 3414 | 3565 | -1138396 |
| **Humanities** | 1973 | 2369 | -2710691 |
| **Total** | | | |
| | chi2(4)= | 197.97 | |
| | Pr>chi2= | 0 | |

## Table 2: Results of the log-polynomial specification.

| Variables | Homogeneous Coefficient | Homogeneous P-value | Normal Mixing Coefficient | Normal Mixing P-value | Gamma Mixing Coefficient | Gamma Mixing P-value | Discrete Mixing Coefficient | Discrete Mixing P-value |
|---|---|---|---|---|---|---|---|---|
| **duration dependence:** | | | | | | | | |
| lnt | -0.3713239 | 0 | -0.3713235 | 0 | 0.137376 | 0.178 | 1.463355 | 0 |
| t2 | 0.005547 | 0.118 | 0.005547 | 0.132 | 0.0131462 | 0.013 | -0.0514121 | 0 |
| t3 | 0.0005625 | 0.017 | 0.0005625 | 0.023 | 0.0012968 | 0.001 | 0.0036226 | 0 |
| **personal characteristics:** | | | | | | | | |
| mobility | 0.0605954 | 0.066 | 0.0605954 | 0.066 | 0.0345276 | 0.558 | 0.1001772 | 0.021 |
| militaryser | -0.4558916 | 0 | -0.4558922 | 0 | -1.142401 | 0 | -0.156995 | 0.019 |
| age | -0.0739731 | 0 | -0.0739732 | 0 | -0.091646 | 0 | -0.085537 | 0 |
| sex | -0.1430251 | 0 | -0.1430253 | 0 | -0.3022407 | 0 | -0.0915983 | 0.078 |
| workduruniversity | -0.0760083 | 0.023 | -0.0760084 | 0.023 | -0.2297479 | 0 | -0.0145281 | 0.742 |
| university final mark | -0.0022069 | 0.365 | -0.0022069 | 0.365 | 0.0028349 | 0.523 | -0.0059673 | 0.058 |
| high school final mark | 0.001732 | 0.486 | 0.001732 | 0.488 | 0.0048935 | 0.275 | -0.0003074 | 0.924 |
| **high school type:** | | | | | | | | |
| general high school | 0.0361103 | 0.528 | 0.0361104 | 0.524 | 0.0561997 | 0.574 | 0.0294945 | 0.69 |
| vocational/tech high school | 0.0425121 | 0.49 | 0.0425122 | 0.485 | 0.1055892 | 0.326 | -0.0025692 | 0.974 |
| **university group:** | | | | | | | | |
| Engineering | 0.1361557 | 0.007 | 0.1361558 | 0.006 | 0.2463231 | 0.007 | 0.1214982 | 0.065 |
| Social sciences | -0.161083 | 0 | -0.1610832 | 0 | -0.2625992 | 0.001 | -0.1299539 | 0.046 |
| Humanities | -0.3469408 | 0 | -0.3469412 | 0 | -0.6209759 | 0 | -0.3199328 | 0 |
| **university (grouped by region)** | | | | | | | | |
| northeast | -0.1305612 | 0.002 | -0.1305614 | 0.002 | -0.2551981 | 0.001 | -0.0793899 | 0.17 |
| centre | -0.2505108 | 0 | -0.2505111 | 0 | -0.4419531 | 0 | -0.1892606 | 0.002 |
| south | -0.497394 | 0 | -0.4973946 | 0 | -1.003321 | 0 | -0.3644468 | 0 |
| **parents' education:** | | | | | | | | |
| parentaleducation2 | 0.0385912 | 0.536 | 0.0385914 | 0.536 | 0.1343415 | 0.232 | -0.006013 | 0.944 |
| parentaleducation3 | 0.1032177 | 0.074 | 0.1032178 | 0.074 | 0.19224 | 0.064 | 0.0780934 | 0.278 |
| parentaleducation4 | -0.0028894 | 0.962 | -0.0028893 | 0.962 | 0.0516643 | 0.624 | -0.0591301 | 0.455 |
| parentaleducation5 | 0.0616191 | 0.342 | 0.0616192 | 0.338 | 0.1315848 | 0.248 | 0.0705464 | 0.397 |
| parentaleducation6 | -0.0926146 | 0.222 | -0.0926146 | 0.216 | -0.0679371 | 0.607 | -0.0754829 | 0.436 |
| parentaleducation7 | 0.0699367 | 0.44 | 0.0699369 | 0.435 | 0.349604 | 0.032 | -0.0604858 | 0.615 |
| **father's occupation:** | | | | | | | | |
| entrepreneur | 0.1391532 | 0.067 | 0.1391534 | 0.067 | 0.4615475 | 0.001 | 0.0471155 | 0.622 |
| professional worker | 0.0643941 | 0.431 | 0.0643941 | 0.426 | 0.2396845 | 0.102 | -0.0191005 | 0.851 |
| own-account worker | 0.0143088 | 0.811 | 0.0143088 | 0.811 | 0.1141972 | 0.287 | -0.0811998 | 0.346 |
| manager | 0.1401497 | 0.049 | 0.1401499 | 0.049 | 0.3404123 | 0.008 | 0.0192349 | 0.842 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| teacher/professor | -0.0112486 | 0.901 | -0.0112485 | 0.9 | 0.0454078 | 0.77 | -0.0296727 | 0.813 |
| white collar high level | 0.1291801 | 0.046 | 0.1291802 | 0.045 | 0.2346982 | 0.041 | 0.1431497 | 0.081 |
| white collar low level | 0.1022502 | 0.138 | 0.1022503 | 0.136 | 0.2853773 | 0.021 | 0.0096954 | 0.918 |
| blue collar high level | 0.0443426 | 0.458 | 0.0443427 | 0.458 | 0.1695161 | 0.117 | 0.0086675 | 0.913 |
| **constant** | 1.449309 | 0.007 | 1.44931 | 0.007 | 2.018419 | 0.04 | | |
| variance | | | | | 1.186 | | 0.1216 | |
| mass point 1 location | | | | | | | 0.28236 | |
| mass point 1 probability | | | | | | | 0.7183 | |
| mass point 2 location | | | | | | | 4.0212 | |
| mass point 2 probability | | | | | | | 0.2817 | |
| no of person-period obs | 18382 | | 18382 | | 18382 | | 18382 | |
| Log-likelihood | -9363.65 | | -9363.65 | | -9327.98 | | -8950.61 | |

**Table 3: Results of the Piecewise Constant Exponential specification.**

| | Homogeneous | | Normal Mixing | | Gamma Mixing | | Discrete Mixing | |
|---|---|---|---|---|---|---|---|---|
| Variables | Coefficient | P-value | Coefficient | P-value | Coefficient | P-value | Coefficient | P-value |
| **duration dependence:** | | | | | | | | |
| quarter 1 | 1.396332 | 0.009 | 1.396334 | 0.01 | 1.491261 | 0.01 | . | . |
| quarter 2-3 | 0.9452248 | 0.079 | 0.9452264 | 0.081 | 1.060764 | 0.068 | 2.241067 | 0 |
| quarter 4-7 | 1.099418 | 0.041 | 1.09942 | 0.042 | 1.24701 | 0.034 | 2.463152 | 0 |
| quarter 8-11 | 1.399149 | 0.01 | 1.399152 | 0.01 | 1.593195 | 0.009 | 2.767759 | 0 |
| quarter >=12 | 2.466148 | 0 | 2.466152 | 0 | 2.721224 | 0 | 3.838766 | 0 |
| **personal characteristics:** | | | | | | | | |
| mobility | 0.0563571 | 0.087 | 0.0563571 | 0.087 | 0.0571556 | 0.097 | 0.0995347 | 0.013 |
| militaryser | -0.4599618 | 0 | -0.4599624 | 0 | -0.4976171 | 0 | -0.1877149 | 0.003 |
| age | -0.0715951 | 0 | -0.0715951 | 0 | -0.0742632 | 0 | -0.0758514 | 0 |
| sex | -0.1443971 | 0 | -0.1443973 | 0 | -0.1556474 | 0 | -0.069465 | 0.15 |
| workduruniversity | -0.0789204 | 0.018 | -0.0789205 | 0.018 | -0.0882735 | 0.015 | -0.0136736 | 0.735 |
| university final mark | -0.0019358 | 0.427 | -0.0019358 | 0.427 | -0.0017881 | 0.484 | -0.0061158 | 0.034 |
| high school final mark | 0.0020806 | 0.404 | 0.0020806 | 0.405 | 0.0023061 | 0.379 | 0.0007023 | 0.811 |
| **high school type:** | | | | | | | | |
| general high school | 0.0334584 | 0.558 | 0.0334585 | 0.555 | 0.0372443 | 0.529 | 0.0554095 | 0.393 |
| vocational/tech high school | 0.0402268 | 0.513 | 0.0402269 | 0.508 | 0.0462647 | 0.468 | 0.0159961 | 0.821 |
| **university group:** | | | | | | | | |
| Engineering | 0.1311232 | 0.009 | 0.1311232 | 0.008 | 0.1326834 | 0.011 | 0.0804768 | 0.194 |
| Social sciences | -0.1601668 | 0 | -0.160167 | 0 | -0.1712497 | 0 | -0.1570826 | 0.007 |
| Humanities | -0.3391952 | 0 | -0.3391955 | 0 | -0.3584985 | 0 | -0.2875712 | 0 |
| **university (grouped by region)** | | | | | | | | |
| northeast | -0.1308441 | 0.002 | -0.1308442 | 0.002 | -0.1403498 | 0.002 | -0.0813967 | 0.134 |
| centre | -0.2519251 | 0 | -0.2519253 | 0 | -0.2673039 | 0 | -0.2011342 | 0 |
| south | -0.4970476 | 0 | -0.4970481 | 0 | -0.529359 | 0 | -0.3429432 | 0 |
| **parents' education:** | | | | | | | | |
| parentaleducation2 | 0.0440601 | 0.48 | 0.0440602 | 0.479 | 0.0494966 | 0.449 | -0.0058518 | 0.937 |
| parentaleducation3 | 0.1019983 | 0.078 | 0.1019984 | 0.077 | 0.1077914 | 0.076 | 0.0561801 | 0.398 |
| parentaleducation4 | 0.0010658 | 0.986 | 0.0010658 | 0.986 | 0.0060523 | 0.923 | -0.0568167 | 0.429 |
| parentaleducation5 | 0.0630304 | 0.332 | 0.0630304 | 0.327 | 0.0678331 | 0.314 | 0.0336632 | 0.662 |
| parentaleducation6 | -0.0911415 | 0.23 | -0.0911415 | 0.223 | -0.0920959 | 0.238 | -0.1092295 | 0.21 |
| parentaleducation7 | 0.0741298 | 0.413 | 0.0741301 | 0.407 | 0.0908353 | 0.34 | -0.1067609 | 0.34 |
| **father's occupation:** | | | | | | | | |
| entrepreneur | 0.1381534 | 0.069 | 0.1381536 | 0.068 | 0.1531335 | 0.059 | 0.00336 | 0.97 |
| professional worker | 0.0657697 | 0.421 | 0.0657697 | 0.416 | 0.0702658 | 0.406 | -0.004108 | 0.965 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| own-account worker | 0.0181939 | 0.761 | 0.018194 | 0.761 | 0.0230814 | 0.712 | -0.0561046 | 0.452 |
| manager | 0.137115 | 0.054 | 0.1371152 | 0.054 | 0.1479736 | 0.049 | 0.0311304 | 0.722 |
| teacher/professor | -0.0058115 | 0.949 | -0.0058115 | 0.948 | -0.003706 | 0.968 | -0.0069444 | 0.95 |
| white collar high level | 0.1254186 | 0.053 | 0.1254187 | 0.051 | 0.1304732 | 0.053 | 0.1137459 | 0.129 |
| white collar low level | 0.1047343 | 0.128 | 0.1047345 | 0.127 | 0.1158522 | 0.111 | 0.0173228 | 0.835 |
| blue collar high level | 0.0409122 | 0.494 | 0.0409122 | 0.493 | 0.0460699 | 0.462 | -0.0313738 | 0.65 |
| variance | | | | | | | 0.1206 | |
| mass point 1 location | | | | | | | -1.0243 | |
| mass point 1 probability | | | | | | | 0.7329 | |
| mass point 2 location | | | | | | | 3.9309 | |
| mass point 2 probability | | | | | | | 0.2671 | |
| no of person-period obs | 18382 | | 18382 | | 18382 | | 18382 | |
| Log-likelihood | -9384.14 | | -9384.14 | | -9383.72 | | -8991.9 | |

## Table 4: Independent Competing Risks model results.

| Variables | Fixed-term contract Coefficient | Fixed-term contract P-value | Open-ended contract Coefficient | Open-ended contract P-value |
|---|---|---|---|---|
| **duration dependence:** | | | | |
| quarter 1 | 0.0528139 | 0.957 | 0.7172376 | 0.349 |
| quarter 2-3 | -0.4518352 | 0.646 | 0.4091341 | 0.594 |
| quarter 4-7 | -0.2567898 | 0.794 | 0.6387147 | 0.409 |
| quarter 8-11 | 0.1864805 | 0.85 | 0.9652161 | 0.22 |
| quarter >=12 | 1.134588 | 0.255 | 2.019738 | 0.013 |
| **personal characteristics:** | | | | |
| mobility | 0.1319883 | 0.017 | 0.007677 | 0.868 |
| militaryser | -0.0681394 | 0.476 | -0.7387421 | 0 |
| age | -0.0826791 | 0.001 | -0.0583311 | 0.004 |
| sex | 0.2075161 | 0.003 | -0.3632243 | 0 |
| workduruniversity | -0.0961502 | 0.089 | -0.0819158 | 0.084 |
| university final mark | -0.00245 | 0.575 | -0.0003559 | 0.916 |
| high school final mark | 0.0029212 | 0.498 | 0.0017133 | 0.624 |
| **high school type:** | | | | |
| general high school | 0.0657697 | 0.461 | 0.014983 | 0.854 |
| vocational/tech high school | 0.074985 | 0.445 | 0.029356 | 0.735 |
| **university group:** | | | | |
| Engineering | -0.1734739 | 0.046 | 0.278211 | 0 |
| Social sciences | -0.3377125 | 0 | -0.0696799 | 0.276 |
| Humanities | -0.122266 | 0.142 | -0.5558422 | 0 |
| **university (grouped by region)** | | | | |
| northeast | -0.0140339 | 0.845 | -0.2089908 | 0 |
| centre | -0.0967604 | 0.23 | -0.3702685 | 0 |
| south | -0.3096046 | 0 | -0.6586075 | 0 |
| **parents' education:** | | | | |
| parentaleducation2 | -0.0895483 | 0.375 | 0.1551497 | 0.083 |
| parentaleducation3 | -0.054915 | 0.56 | 0.2107057 | 0.011 |
| parentaleducation4 | -0.0609184 | 0.528 | 0.0548163 | 0.521 |
| parentaleducation5 | -0.1448043 | 0.179 | 0.1931947 | 0.034 |
| parentaleducation6 | -0.2064596 | 0.099 | -0.000982 | 0.993 |
| parentaleducation7 | -0.127923 | 0.405 | 0.2481774 | 0.052 |
| **father's occupation:** | | | | |
| entrepreneur | -0.0597728 | 0.649 | 0.3134268 | 0.004 |
| professional worker | -0.2552855 | 0.076 | 0.264883 | 0.018 |
| own-account worker | -0.0534574 | 0.575 | 0.0735499 | 0.392 |
| manager | 0.0189445 | 0.873 | 0.2340791 | 0.02 |
| teacher/professor | -0.0248452 | 0.867 | 0.0326851 | 0.795 |
| white collar high level | -0.0583722 | 0.589 | 0.2527128 | 0.006 |
| white collar low level | -0.0156941 | 0.89 | 0.2116538 | 0.032 |
| blue collar high level | 0.0110923 | 0.907 | 0.0775643 | 0.369 |
| no of person-period obs | 18382 | | 18382 | |
| Log-likelihood | -4973.994 | | -7311.64 | |

| | first job | | | |
|---|---|---|---|---|
| **status** | noexit | exit | Total | **mean duration** |
| unemployed | 100 | 0 | 17.86 | 16 (0) |
| fixed-term | 0 | 35.6 | 29.24 | 4.6 (3.9) |
| open-ended | 0 | 64.4 | 52.9 | 4 (3.5) |
| | 17.86 | 82.14 | 100 | |

## Appendix: Definitions of the covariates and sample averages.

| Name and definition | Average |
|---|---|
| Time (in quarters, from 0 to 16) | 7.204209 |
| Mobility (1, transfer in another region; 0 otherwise) | 1.493919 |
| Sex (0, male; 1, female) | 1.522089 |
| Military service (0, done before degree or exempted from; 1, done after degree) | 0.1592793 |
| Age | 28.41297 |
| University final mark (integers from 66 to 110) | 102.615 |
| High school mark (integers from 36 to 60) | 48.81282 |
| General high school | 0.5913778 |
| Vocational/technical high school | 0.2902523 |
| Other high school | 0.1183699 |
| Workduruniversity (1, the graduate held at least one job during university studies, 0, otherwise) | 0.434408 |
| Parentaleduc1 (both parents illiterate or with primary school certificate) | 0.1461798 |
| Parentaleduc2 (at least one parent with middle school certificate) | 0.0978303 |
| Parentaleduc3 (both parents with a middle school certificate) | 0.148035 |
| Parentaleduc4 (at least one parent with a high school certificate) | 0.1897102 |
| Parentaleduc5 (both parents with high school certificate) | 0.175728 |
| Parentaleduc6 (at least one parent with a degree) | 0.1605014 |
| Parentaleduc7 (both parents with a degree) | 0.0820154 |
| North-west (university in the north-west of Italy) | 0.2653061 |
| North-east (university in the north-east of Italy) | 0.2398695 |
| Centre (university in the centre of Italy) | 0.2396883 |
| South (university in the south of Italy) | 0.255136 |
| Scientific (graduation in scientific subjects) | 0.2277312 |
| Engineering (graduation in engineering) | 0.1953137 |
| Social sciences (graduation in social, economic and political subjects) | 0.3496057 |
| Humanities (graduation in humanities) | 0.2273493 |
| entrepreneur | 0.0531305 |
| professional worker | 0.079752 |
| own-account worker | 0.1284793 |
| manager | 0.1402062 |
| teacher/professor | 0.0636443 |
| white collar high level | 0.1586952 |
| white collar low level | 0.0943994 |
| blue collar high level | 0.1373981 |
| other occupation | 0.15166 |