Do Training Programmes get the unemployed back to work?: A look at the Spanish experience[¤]

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Abstract

This work studies the e¤ect of some training courses for economic disadvantaged and unemployed people elaborated by Spanish National Institute of Employment (INEM) in terms of the consecution of a job. Two groups of Spanish unemployed people are compared between April of 2000 and February of 2001, one of them did training courses in the …rst quarter of 2000. Non-parametric techniques, parametric and semi-parametric continuous time duration methods are used to analyze this relationship. The results suggest a higher positive e¤ect of some training courses for women than for men, specially in the case of those receiving some kind of economic help. Furthermore, young unemployed people and unemployed people with a reduced period of active labour demand have higher exit rates to a job. However, education and disabilities do not a¤ect signi…cantly the exit rate to a job.

PRELIMINAR WORK
(do not quote without permission)

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1 Introduction

Governments spend great amounts of resources, basically from taxes, to develop social programmes and other public activities. Di¤erent groups better o¤ and worse o¤ with such programs. The study of these pro…ts and losses plays an important role on the public decision taking.

For analytical and policy purposes, the OECD splits this spending into so-called active and passive measures where the former comprise a wide range of policies aimed at improving the access of the unemployed to the labour market and jobs, job-related skills and the functioning of the labour market while the latter relate to spending on income transfers.

Public expending on active labour market programmes absorbs signi…cant shares of national resources in most of the OECD countries. It supposes more than a third of the total resources dedicated to unemployment bene…ts, in some countries it exceeds such bene…ts. Table 1 shows a wide variation across EU countries in the share of the main categories of labour market programmes. The OECD data base covers …ve main categories of these programs: Public employment services and administration, youth measures, subsidized employment, measures for the disabled and labour market training[1]. This last category constitutes one of the more attractive (and expensive) paradigms in public interventions. The weight of these policies with respect to GDP is a incomplete measure of the e¤ort done in each country; alternatively, the resources dedicated to each unemployed appear in the last two rows. Spain jointly with U.K. and Greece dedicate less quantity of resources to (active) labour market policies.

	Austria	Belgium	Denmark	Finland	France	Germany	Greece	Netherlands	Portugal	***Spain***	Sweden	U.K.
1. Public employment services and administration	0,14	0,17	0,12	0,12	0,18	0,23	0,06	0,26	0,11	**0,09**	0,23	0,13
2. Labour market training	0,20	0,24	0,85	0,29	0,25	0,34	0,21	0,31	0,15	**0,14**	0,30	0,05
3. Youth measures	0,03	-	0,10	0,16	0,42	0,09	0,10	0,04	0,22	**0,06**	0,02	0,15
4. Subsidised employment	0,11	0,77	0,17	0,29	0,37	0,25	0,08	0,38	0,09	**0,40**	0,24	0,01
-Hiring subsidies	0,06	0,27	0,02	0,15	0,18	0,03	0,05	0,05	0,01	**0,25**	0,19	0,01
5. Measures for the disabled	0,06	0,12	0,33	0,09	0,09	0,29	0,01	0,58	0,04	**0,03**	0,31	0,02
Active measures (from 1 to 5)	0,53	1,30	1,56	0,95	1,31	1,20	0,46	1,58	0,61	**0,73**	1,09	0,36
Passive measures (*)	1,07	2,18	3,00	2,02	1,65	1,92	0,47	1,86	0,90	**1,33**	1,19	0,56
Labour market policies	1,60	3,48	4,56	2,96	2,96	3,13	0,93	3,44	1,52	**2,06**	2,28	0,92
Labour market policies for one point of unemployment rate	0,44	0,53	1,06	0,33	0,34	0,40	0,12	1,43	0,37	***0,16***	0,45	0,18
Active policies for one point of unemployment rate	0,15	0,22	0,36	0,10	0,15	0,15	0,06	0,66	0,15	***0,06***	0,21	0,07

(*) It includes unemployment benefits and early retirement pensions for labour market reasons.
Source: OECD, Employment perspectives, June 2002

Table 1: Spending on labour market programmes in EU countries, 2001

[1] More information about public spending on labour market programmes in Martin (2000).

Considering the five main categories, apart from subsidized employment, labour market training is the most important labour market programme in Spain. Taking into account these figures, the objective of this work concerns the study and evaluation of a labour market training programme that the National Institute of Employment (INEM), or the autonomous region with the corresponding competence, carries out annually in Spain: the National Plan for Training and Professional Insertion. It was included as one of the labour market actions defined by the Spanish government in 1980, but its original structure comes from the rearrangement of training to lay stress on professional reinsertion of unemployed people from 1993. Although all unemployed people can profit from these courses, the plan includes a preferable set of collectives:

- Unemployed workers receiving any kind of unemployment benefits.
- Long-term unemployed above 25 years of age (over 1 year of registered unemployment).
- Young unemployed workers (under 25 years of age) who lost a job of at least 6 months.
- Women who want to work.
- Disabled workers.
- Migrant workers.

The management and planning of programmes, and preselection of candidates corresponds to INEM or autonomous regions with the corresponding competence The selection of individuals depends on people who carry out the courses. If some conditions are satisfied, any institution can be a center in which training is carried out. Once an individual passes correspondent evaluations, he obtains an official professional certificate. There are four levels depending on the objective of the courses:

- Course 1: Broad basis. Courses appointed preferably to youth in order to provide knowledge and skills to facilitate their insertion in the labor market, but these courses do not provide a specific qualification for an occupation.
- Course 2: Occupation. Courses assigned to unskilled people in order to provide knowledge and skills to hold an occupation.
- Course 3: Specialization. Courses appointed to skilled workers who need to train for a new occupation.
- Course 4: Adaptation-Occupation. Courses assigned to improve and bring up to date knowledge to skill workers such that they can be promoted to a superior level of jobs.

This plan does not belong neither to the Educational System, which depends on the Spanish Ministry of Education, nor the training dedicated to workers, controlled by FORCEM[2].

Considering the previous environment, the work has the following structure: a descriptive analysis of data base is done in Section 2. In Section 3 non-parametric techniques are applied to obtain preliminary information about data and each of the variables. In order to study the relationship of the variables in data, parametric and semi-parametric techniques are used in Section 4. Section 5 comments conclusions and extensions.

[2] FORCEM is the Fundation for Continuous Training, constituted by empresarial organizations and unions in May of 1993. It takes charge of driving and spreading Continuous Training among …rms and workers, promoting assistance, and controlling this activity.

2 Data

Data used for this study are provided by INEM. They are distributed in three ...les: (i) a ...le constituted by active employment demand people, who are controlled in three moments of time (31 March 2000, 30 September 2000, 31 March 2001); (ii) other ...le in which treatment group appears; and ...nally (iii) a group of contracts along the period between 31 march 2000 and 31 march 2001.

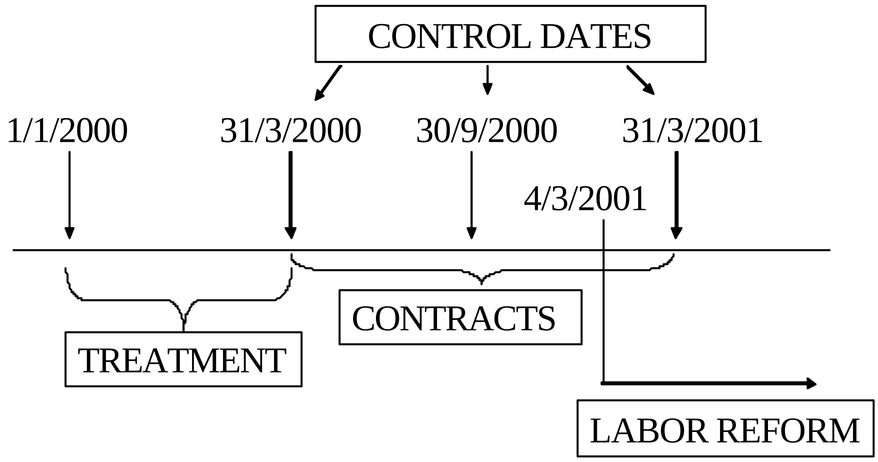

Figure 1: Evolution of data

From each individual we have the corresponding spell between 31 March 2000 and 31 March 2001. Unfortunately, there exist some limitations in terms of individuals and the period of time. The initial sample is constituted by 55,261 (random selected) individuals. However, it is necessary to eliminate all individuals who do not dispose of all variables and at least two consecutive control dates (including the day of obtaining a job). In order to establish a relative homogenous sample, we also get rid of all non-active labour demand, non-unemployed people at 31 March 2000, and people who are higher than 60 years old and have an active labour demand more than 2,000 days.

Moreover, this subsample is reduced because of some limitations from censored data[3]. Data with censorship at 30 September 2000 is eliminated. Com-

[3] Considering the theory exposed by Miller (1981) and Kalb‡eisch and Prentice (1980), all censoring data (at 28/2/2001) present Type I censorship, because the experiment ...nished at this day.

Miller (1981) considers this assumption is valid in the case of random losses to follow-up, as it is supposed in this work. Although it seems that problems of estimation do not exist, it would be necessary to consider asintotic results with Type I censorship if con...dence intervals and tests were used. A possible solution consists of creating two data base depending on elimination of censored data at 30/9/2000. After doing estimates with two samples, there are no important di¤erences between both.

paring the results with and without this set of individuals, they do not vary substantially.

The final sample is now constituted by 19,941 individuals, part of them (7,517 individuals) did a training course in the first quarter of year 2000.

With respect to the period of study, it is reduced because of the application of an important labour reform at 4 March 2001. This labour reform introduced urgent measures to increase and better off the quality of employment, given the high use of temporary contracts[4]. The measure consisted of extending a new permanent contract with smaller dismissal costs introduced at 1997 to other groups of people. Instead of the existing permanent contract, with 20 days' wages per year of seniority with a maximum of 12 months' wages in the case of fair dismissals, and 45 days' wages per year of seniority with a maximum of 42 months' wages in the case of unfair dismissals, the new permanent contract allows a reduction of 33 days' wages per year of seniority with a maximum of 24 months' wages in the case of unfair dismissals. In order to avoid collateral effects of this measure in the sample, the period of study is limited to 28 February 2001. The group of individuals affected by this reduction is minuscule (around 1% of the sample).

All initial variables used in this work are defined in Appendix A. A descriptive analysis of these variables appears in Table 1 and 2 considering all the sample, and the treatment and control groups:

Variables	Total	Treatment	Control
% woman	60.70	64.02	58.69
	(0.49)	(0.48)	(0.49)
age	30.26	30.11	30.34
	(10.00)	(9.04)	(10.54)
% Level of education 4	40.12	38.53	42.29
% Disabled	2.13	2.00	2.20
	(0.14)	(0.14)	(0.15)
% No Benefits	66.05	68.39	64.63
% from Madrid	26.90	46.18	15.24
% from provinces $>$ 1,000,000	55.23	60.49	52.03
% White-collar workers	21.52	24.70	19.60
% Restaurant workers, protection and sellers	22.12	19.40	23.77
Days of active demand	338.86	356.04	328.46
	(368.15)	(382.46)	(358.83)
N	19,941	7,517	12,424

Table 1: Descriptive statistics[5]

[4] For a resume about Spanish labor market reforms, see Kugler, Jimeno and Hernanz (2002).

[5] The table reports means and percentages for the indicated group. Standard deviations are in parenthesis where appropriate.

In general terms, figures show some kind of homogeneity between treatment and control group, except for the province of residence, because there is a higher concentration around Madrid for treatment group than for control group, and the economic activities in which individuals desire to work as their first preference, where weights of the most important economic activities are changed.

MEN			
Variables	Total	Treatment	Control
age	31.58	29.87	32.49
	(11.05)	(9.63)	(11.64)
% Level of education 4	42.98	41.72	43.65
% Disabled	3.29	3.18	3.35
	(0.18)	(0.18)	(0.18)
% No Benefits	56.67	62.65	53.53
% from Madrid	28.87	51.41	16.99
% from provinces $>$ 1,000,000	64.36	72.86	59.88
% White-collar workers	13.17	13.28	13.11
% Restaurant workers, protection and sellers	10.55	10.65	10.50
Days of active demand	301.99	292.26	307.11
	(348.83)	(344.90)	(350.81)
N	7,836	2,704	5,132

WOMEN			
Variables	Total	Treatment	Control
age	29.40	30.26	28.83
	(9.15)	(8.69)	(9.39)
% Level of education 4	38.27	33.62	41.33
% Disabled	1.38	1.35	1.40
	(0.12)	(0.12)	(0.12)
% No Benefits	72.12	71.62	72.45
% from Madrid	25.63	43.24	14.00
% from provinces $>$ 1,000,000	56.08	59.68	53.72
% White-collar workers	26.93	31.12	24.16
% Restaurant workers, protection and sellers	29.61	24.31	33.10
Days of active demand	362.73	391.87	343.49
	(378.24)	(397.60)	(363.65)
N	12,105	4,813	7,292

Table 2: Descriptive statistics by gender

When men and women are compared, previous differences between treatment and control group are maintained. Although basic characteristics appear in both groups, women select jobs related to services sector and men prefer industry. In addition, the weight of disabled, less educated people and living in the most populous provinces is higher for men than for women. The opposite occurs with people without benefits and the days of active labour demand.

3 Non-parametric estimates of survivor functions

3.1 Introduction

Using the information derived from data, the objective of this section consists of the estimation of survivor functions. Let T be a non-negative random variable representing the waiting time until the occurrence of an event (e.g. obtaining a job). We will assume that T is a continuous random variable with probability density function $f(t)$ and cumulative distribution function $F(t)$, whose complement is the **survivor function** $S(t) = 1 - F(t)$. An alternative characterization of the distribution of T is given by the **hazard function**, or instantaneous rate of occurrence of the event, defined as

$$h(t) = \lim_{dt \to 0} \frac{P[t \leq T < t + dt \mid T \geq t]}{dt}$$

where the numerator is the conditional probability that the event will occur in the interval $(t, t + dt)$ given that it has not occurred before, and the denominator is the width of the interval. The former expression may be written as

$$h(t) = \frac{f(t)}{S(t)}$$

Given this result, $h(t)$ may be estimated using an estimation of $F(t)$ or $S(t)$. Then the nonparametric maximum-likelihood estimate of the survivor function is (Kaplan and Meier, 1958)

$$\hat{S}(t) = \prod_{j \mid t_j \leq t} \left(\frac{n_j - d_j}{n_j} \right)$$

Let n_j be the population waiting a change of event at time t_j and d_j the number of changes at t_j.

Kaplan-Meier estimates are used taking into account that the moment of occurring an event corresponds to the day in which the individual obtains a job.

3.2 Kaplan-Meier estimates

Estimates of survivor functions are represented in the following figures of this section. Probability appears in vertical axis and time in months in horizontal axis.

In Figure 1, Kaplan-Meier estimate of the survivor function from total sample appears jointly with the number of spells affected by right censorship at the termination of the study. The introduction of con…dence intervals by Greenwood's formula does not generate important di¤erences in this …gure, because the con…dence intervals are near the estimate.

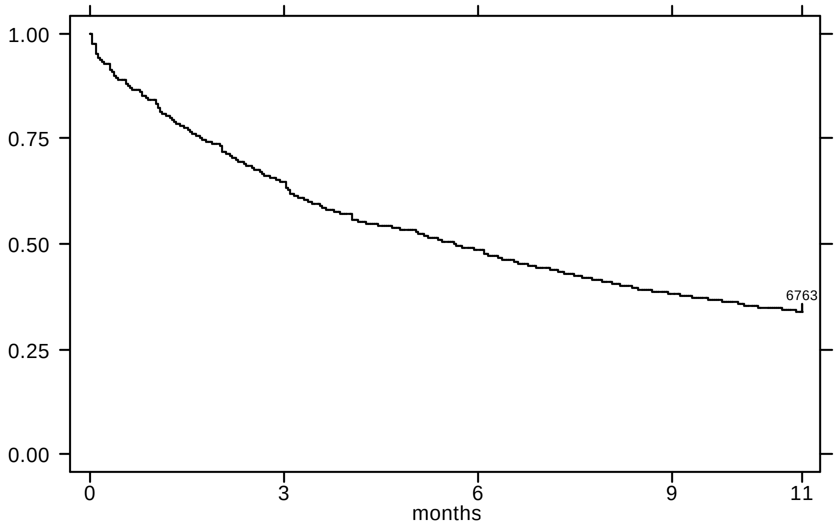

Figure 1: Kaplan-Meier estimate

However, the estimates may contain bias if a set of conditions are not satis…ed, such that the existence of a great amount of censoring points and the lack of independence of the sample (due to implicit factors) or such points.

Given that the problem of non-independent censored points was solved, it is possible to control implicit factors partially using di¤erent covariates:

² Considering the treatment, the probability of not obtaining a job before any moment of time is higher for control group than for treatment group, as it can be seen in Figure 2:

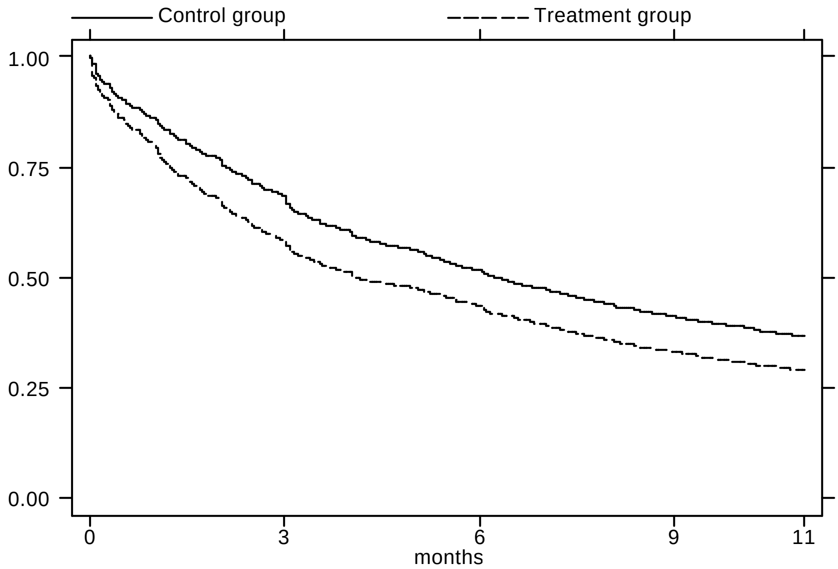

Figure 2: Considering treatment

² With respect to gender, Figure 3 shows one of the facts of the Spanish labour market: women have more probability to maintain the situation of unemployment than men.

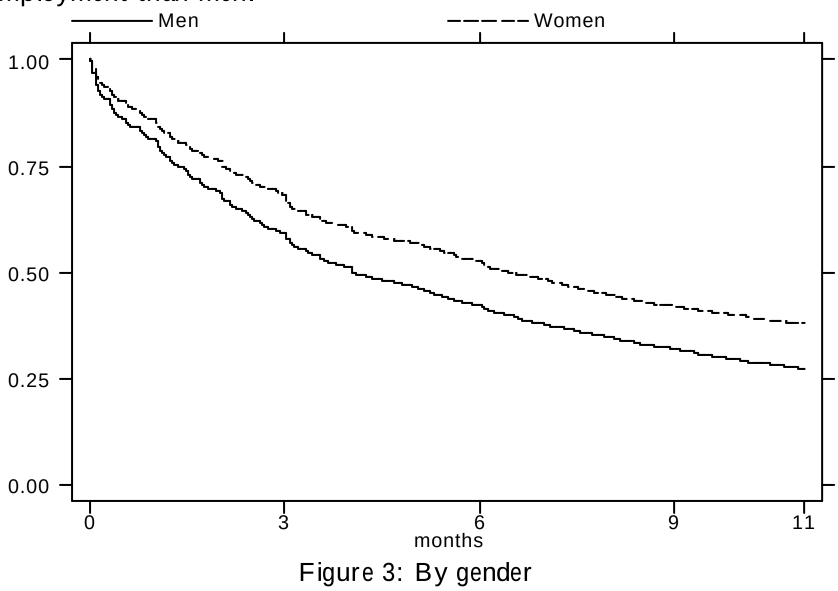

Figure 3: By gender

² Distinguishing among several levels of education in Figure 4, important di¤erences may be noticed. The worst groups are the people less educated

($levestu0$ and $levestu1$). However the best group is associated to the most quali…ed Vocational Training ($levestu7$). The di¤erences in the rest of levels of education is less signi…cative: Group 2 is constituted by $levestu2$, $levestu3$, $levestu6$ and $levestu9$ and Group 3 by $levestu4$, $levestu5$ and $levestu8$. In conclusion, there is no clear linear relationship between education and possibility to abandon unemployment.

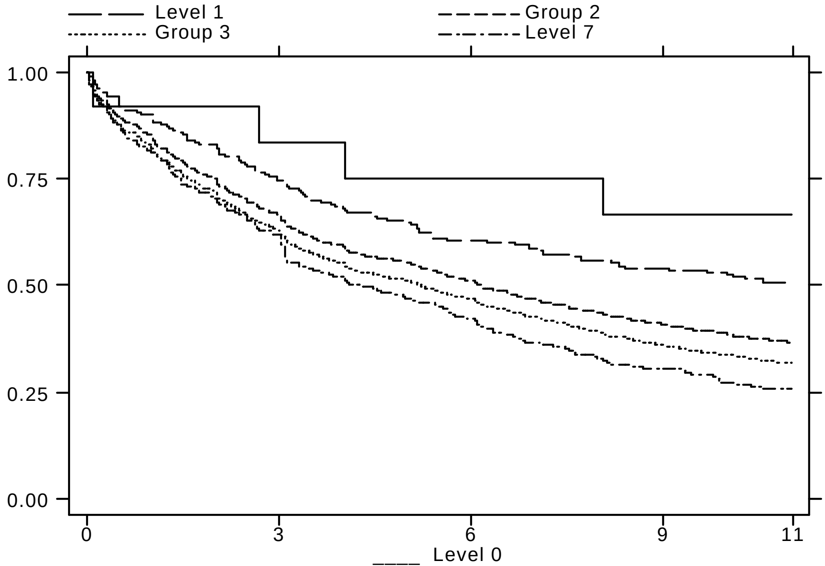

Figure 4: By levels of education

[2] The variable age is divided in six groups in order to show in a better way the e¤ect of age on the probability of changing the situation of unemployment: [16,19], [20,24], [25,29], [30,39], [40,49] and more than 49 years old. There exists an inverse relationship between an increase of the age and the probability of …nding a job, specially in the case of the oldest groups. Moreover, two great groups can be observed in Figure 5, if age is less than 30 years or not.

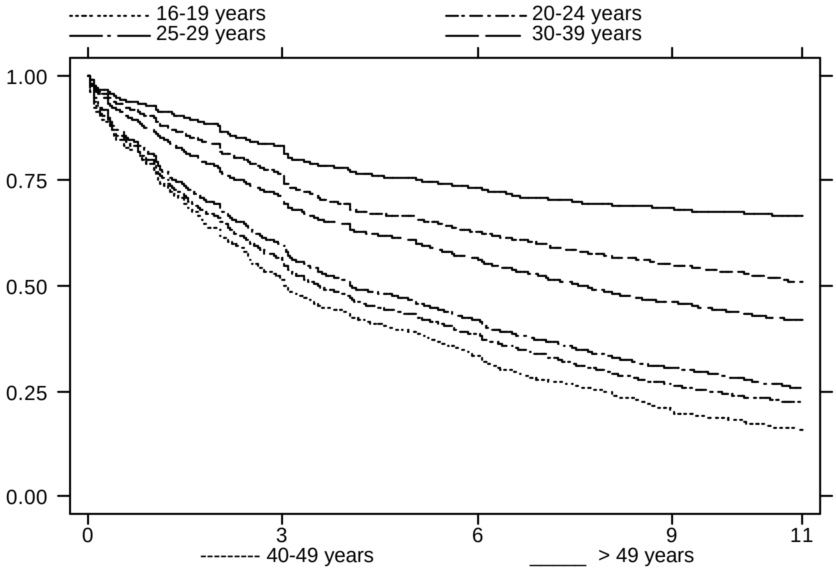

Figure 5: By groups of age

- Another interesting variable is the existence of disabled people. Figure 6 presents the estimates distinguishing between disabled and non disabled. The result is in favour of the latter group:

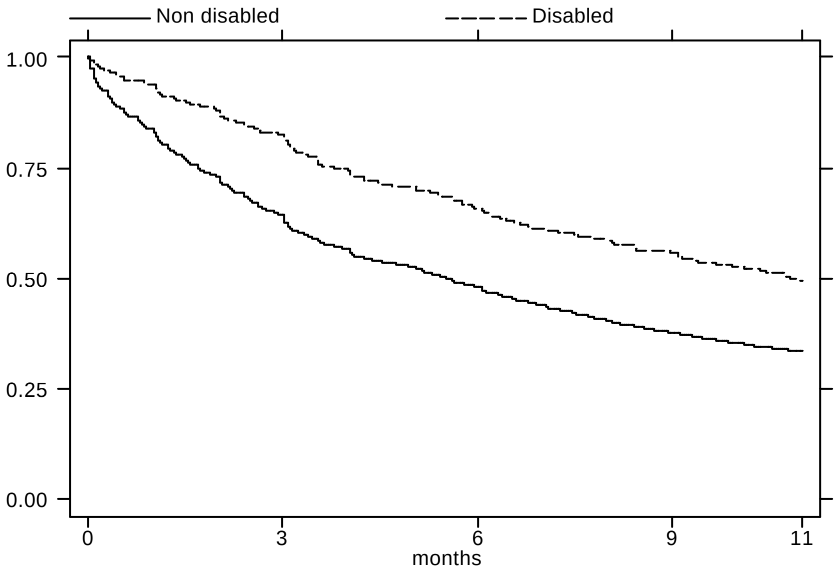

Figure 6: Considering the existence of disablement

- A variable related to the possibility of receiving some kind of bene…t in the moment of control is also disposal, as it can be seen in Figure 7:

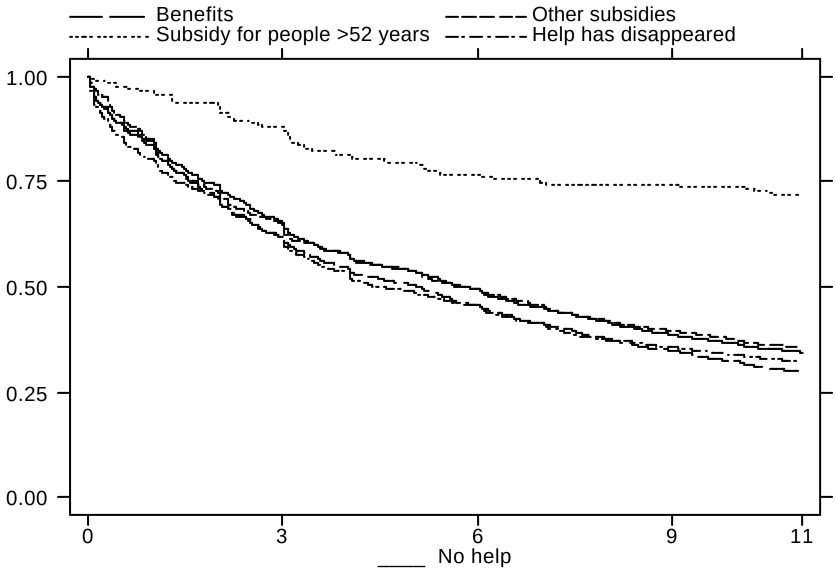

Figure 7: By bene…ts

The group with more probability to be unemployed is the people who receive bene…ts for individuals more than 52 years. This result is consequent with the previous comment of the variable age.

² With respect to geographic characteristics, it is more di¢cult to obtain a …gure of all provinces. Figure 8 presents the most important results. Although there is no a clear relationship between rich provinces and an increase of the probability of abandon unemployment, it is necessary to distinguish between the best behaviour of Baleares Islands and $Group$ 3[6] and the worst, associated to Melilla and Palencia. Apart from these provinces, the di¤erences among the rest of them are relatively limited, but it is possible to distinguish between provinces belonging to $Group$ 1[7] and the other provinces in $Group$ 2[8].

[6] $Group$ 3 is composed by $prov$12 (Castellón), $prov$19 (Guadalajara), and $prov$22 (Huesca).

[7] $Group$ 1 is composed by $provX$ when X =1, 4, 5, 8, 9, 15, 16, 17, 20, 25, 26, 27, 30, 31, 35, 36, 38, 39, 40, 42, 43, 44, 45, 47 and 50 (see index in Appendix A).

[8] $Group$ 2 is composed by $provX$ when X = 2, 3, 6, 10, 11, 13, 14, 18, 21, 23, 24, 28, 29, 32, 33, 37, 41, 46, 48, 49 and 51 (see index in Appendix A).

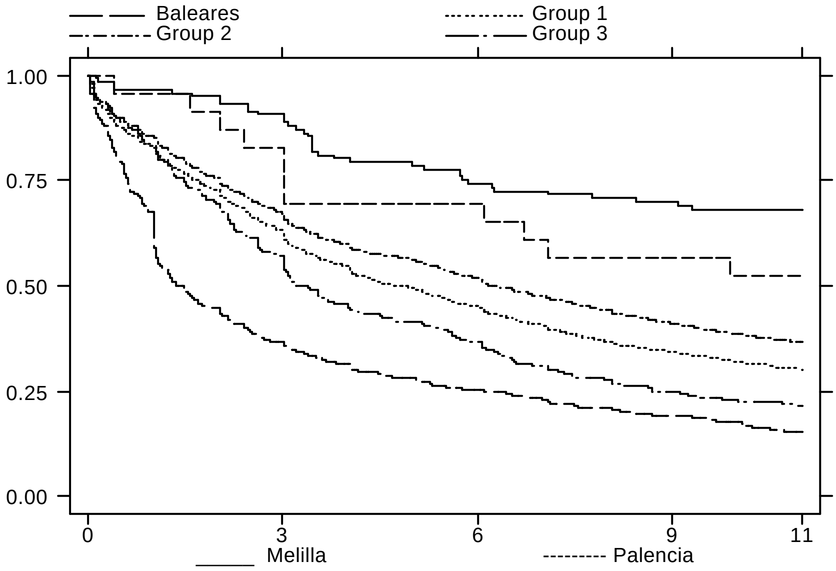

Figure 8: Considering provinces

[2] If we divide the days of active labour demand in several intervals, the positive relationship between active labour demand and the probability to be unemployed is clearly observed. Besides, the di¤erences are higher when the period of active demand increases (Figure 9).

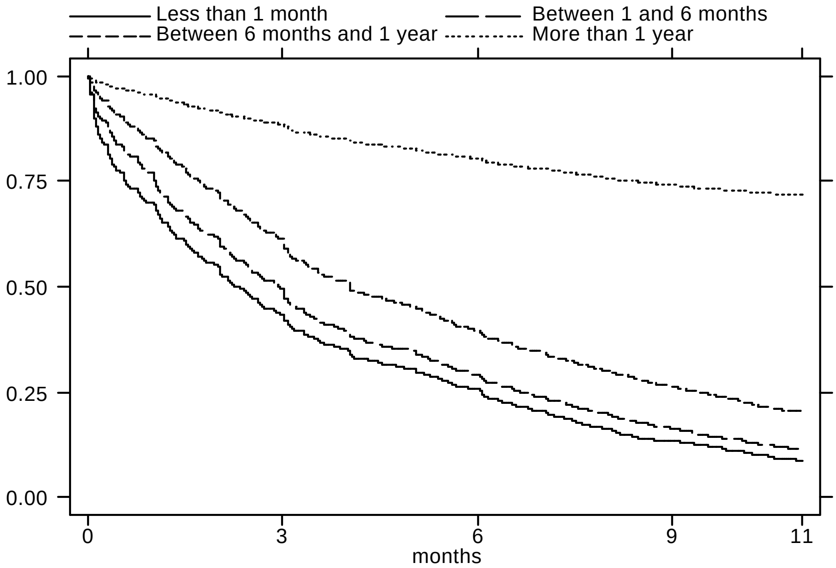

Figure 9: By active labour demand

² Finally, Figure 10 presents the economic activity of the job the individual applied for as …rst option. We establish a previous classi…cation of economic activities, such that $Group$ 2 is formed by $group2$, $group3$, $group5$, $group8$ and $group9$, and $Group$ 3 is constituted by $group0$, $group6$ and $group7$. The worst option is Management and Public Administrations($group1$) and the rest of groups do not show important di¤erences, although $Group$ 3 is the best group versus White-collar workers ($group4$).

Figure 10: By economic activity of the job

Adjustments and comparison of survivor functions are realized, controlling the estimates of the survivor functions for each variable. The reasons are the same as presented ones in the previous …gures, lack of independence and censorship[9].

Considering all possible combinations with respect to adjustments, the number of important adjustments is small, only the variables age and $ddays$ introduce the most important adjustments[10] in survivor function estimates.

[9] If censoring time is not independent of survival time, the estimates of the survivor function will be overestimated if individuals who disappear have great probability to be hired, or underestimated if individuals who disappear have reduced possibility to …nd a job.

[10] Important adjustments are not movements in curves, but the di¤erences among groups are clearly reduced. Given this fact and the relatively high number of groups for each variable, conlusions are reasonable.

Often it is of interest to determine whether two or more samples could have arisen from identical survivor functions. An alternative to adjustments and graphic solutions is testing the similarity of groups for each variable. The tests belong to a family of test statistics which are extensions of non-parametric rank tests to compare two or more distributions for censored data[11]. Any of them tests the null hypothesis:

$$H_0 : h_1(t) = h_2(t) = \ldots = h_k(t) \quad \text{for all } t.$$

where $h(t)$ is the hazard function at time t, against the alternative hypothesis that at least one of the functions is different for some t.

Results are consistent with conclusions from figures. All tests confirm the statistical inexistence of similarity among groups for each variable, independently of the most usual confidence intervals (at 99%, 95% and 90%). In the case of curves adjusted for all the combinations of variables, the conclusions are similar to the case without adjustments, and compatible with those derived from graphical study.

[11] The Mantel-Haenszel test (also known as log-rank test), the Breslow test (also known as generalized Wilcoxon test), the Tarone-Ware test and the Peto-Peto-Prentice test. More information in Miller (1981).

4 Parametric and semi-parametric studies

4.1 Introduction

Up to now, data have been used to calculate the probability that an event will occur before time t conditional on each of the characteristics of people.

In this section the objective lies in fitting the survivor function from data base using all together covariates of the study. At first, there exist two models to achieve our objective:

- Accelerated Failure-Time (AFT) models.
- Semi-parametric models: Proportional Hazard rate (PH) models.

Both models can be considered as particular cases of so-called Mixed Proportional Hazard rate (MPH) models. Although parametric versions of the model are included in statistical packages, they are not necessary for specification and identification, as van den Berg (2000) points out.

4.2 AFT models

In spite of difficulties and limitations of AFT models, van den Berg (2000) points out the utility of these models:

"From an econometric point of view, the AFT approach is unsatisfactory, because it does not focus on the parameters of the individual hazard as the parameters of interest. However, if one is only interested in the sign or significance of a covariate effect on the individual durations then the AFT approach may be useful."

The definition of T is the same as the previous section. Let x be a finite-dimensional vector of observed explanatory variables (or covariates), and b be a vector of regression coefficients. We assume, as van den Berg (2000) and van Ours (2001) point out, that there is not neither unobserved heterogeneity among individuals affecting the hazard function, nor anticipation in individuals' decisions, and all individuals are mutually independent.

Linear regression models are connected to hazard models through AFT models. Suppose that $Y = \ln T$ is related to x via a linear regression model:

$$Y = x'b + z \quad (1)$$

where z is the error term with density function $f(\cdot)$.

Exponentiation of (1) gives

$$T = \exp(x'b)T'$$

where $T' = \exp(z)$ has hazard function $h_0(t')$ independent of b. Hence, the hazard function for T can be written in terms of this baseline hazard function $h_0(\cdot)$

$$h(t, x) = h_0(te^{-x'b})e^{-x'b}$$

This models specifies that the effect of the covariates is multiplicative on t rather than on the hazard function as in PH models. The role of the covariates is to change (accelerate or decelerate) the time to failure.

The distributional form of the error determines the regression model. Six parametric survival distributions are used in this work: exponential, log-logistic, log-normal, Weibull, generalized gamma and Gompertz[12].

The models proposed in this study are defined as

$$\begin{aligned} y &= \ln t = x'b + af + z && \text{in the general case} \\ y_i &= \ln t_i = x_i'b_i + a_i f_i + z_i && \text{for each course } i = 1, 2, 3, 4 \end{aligned}$$

The set of covariates for general model is constituted by the variable $treatment$, identified by f (for f_i , $i = 1, 2, 3, 4$ when each course is considered independently) and the rest of covariates in the vector x, all defined in Appendix A.

Let $f(\cdot)$ and $S(\cdot)$ be the appropriate distributions for the desired parametric regression model. Assume that there are N individuals, U of whom have uncensored times. The full log-likelihood function that should be maximized to estimate the parameter vector v and the covariate coefficients vector b is:

$$\ln L = \sum_{j=1} \ln\{f(t_j, v \mid t_{0j})\} + \sum_{j=U+1} \ln\{S(t_j, v \mid t_{0j})\} \tag{2}$$

where a subject known to fail at t contributes to the likelihood function $f(t_j, v \mid t_{0j})$, the value of the density at t conditional on the entry time t_0, whereas a censored observation, only known to survive up to t, contributes $S(t_j, v \mid t_{0j})$, the probability of surviving beyond t conditional on the entry time t_0. Censorship is considered as non-informative[13].

[12] More information about these distributions in Kalbfleisch and Prentice (1980).

[13] Conditions for censored data in order to do a valid study are discussed in Miller (1981) and Kalbfleisch and Prentice (1980).

4.2.1 Results from estimation

The …nal models are formed by the variables de…ned in Appendix A and products of themselves, in order to study the e¤ect of the interaction between covariates. Using the individual signi…cance tests, di¤erent levels are taken into account, 90%, 95% and 99% con…dence levels.

Basic signi…cant estimates with their associated standard deviations for some groups of variables appear in Appendix B[14]. Several regressions are shown depending on the set of individuals and the treatment. In Table B1, the …rst column of estimates considers all the sample and the second and third column presents estimates for men and women, distinguishing only between a treatment and control group. In TableB2 and TableB3, males and females are analyzed taking into account the four levels of treatment.

Firstly, before estimating some variables were eliminated because of problems of collinearity associated to dummy variables. First value of each covariate is disappeared, that is $group0$, $levestu0$, $benefit0$ and so on, except in the case of provinces, where the variable eliminated was $prov28$ (Madrid). Therefore, all estimates are associated to these covariates.

The interpretation of the coe¢cients is complex, because almost all covariates are discrete. However the signs of the coe¢cients may be interpreted and the quantities among covariates of the same group can be compared among them. If the sign is positive, the corresponding covariate increases the duration in unemployment. Otherwise, duration is reduced.

An interesting point is the consistency of signs of estimates in all AFT and PH models, at least in the case of those statistically di¤erent from cero, as tables in Appendix B and C show.

With respect to interpretation of estimates we derive the following conclusions:

Considering gender, the fact to be a woman does not a¤ect to maintain the unemployment situation[15]. This conclusion is not apparently related to the reality of Spanish labour market, where female unemployment rate is signi…cantly higher than male one.

With respect to age, the e¤ect is positive and statistically di¤erent from cero in all models. This e¤ect is linear when women are examined, and non-linear in the cases of men. From supply's point of view, experience is not rejected as a good factor to be hired; however, job o¤ers may not need a high level of

[14] All estimates of models are available on request.

[15] Although the sign varies depending on the model, negative in general model, positive if only levels of training are introduced.

experience. In addition, it is more pro…table to prepare a young person than an old one, because the former has a higher expectancy of labour life than the latter. From demand's point of view, young people accept any o¤er before than adult people.

The level of education do not generate important e¤ects on exit of unemployment. The same conclusion can be established when education is combined with gender or treatment. A possible justi…cation may be the speci…c and limited know-how of job o¤ers, such that no level of education is better than other. Hence, education cannot be interpreted as a signal and can be perfectly substituted by experience.

An interesting conclusion is derived from coe¢cient of disability. Although it is positive, the value is not far enough from cero except for men. In that case, the e¤ect is important, so there exists some kind of di¤erentiation by gender in order to obtain a job between people with and without disability.

The e¤ect of bene…ts on the fact to obtain a job is negative when they are signi…cant, but the group a¤ected depends on gender. Considering women, the people whose bene…t has been disappeared by any reason. Therefore, whether a woman does not have any source of resources, she tries to be hired faster than others. For men, the variable is $benefit$63, that is, people receiving bene…ts. This help can introduce some kind of safety in order to obtain a job before.

The economic activity of the job each individual would like as …rst option does not a¤ect to reduce the period of unemployment in general. However the combination of level of education and economic activity generate some significant positive e¤ects to be unemployed more time when we combine levels of education associated to the most appropriate economic groups to this level of education. However, there is no a common group of signi…cant variables in the models, indicating di¤erences and peculiarities in each subsample.

The local factor depends on the province where the individual lives. Some general conclusions are similar to Kaplan-Meier estimates, specially in qualitative terms: the worst provinces to be hired before are Melilla, Palencia and Ceuta versus Baleares Islands, for example (although there may exist other provinces with better result than Baleares). It appears that rich provinces tends to obtain better results than poor ones, but we cannot con…rm a clear economic relationship between provinces with good and bad estimates according to GDP per capita.

The e¤ect of days of active labour demand is relatively small in absolute value but signi…cantly di¤erent from cero. Taking into account that this covariate belongs to the interval [0, 2000], the di¤erences among individuals may be substantial. This variable implies a stigma the more time in active demand, the more complicated to be hired.

Finally, the effect of treatment is not different from cero, although it is negative for men and positive for women (the significant estimate of the combination of treatment and gender confirms the result), so training implies a higher reduction in the situation of unemployment for women than for men. However this effect is not so clear when different levels of training are analyzed, except for the combination between treatment and benefits, where the results confirm the previous conclusion at least for courses 2 and 3.

4.2.2 Selection of model

There exist several ways to select some of the proposed models. When parametric models are not nested, a common approach is to use Akaike information criterion (AIC)[16].

Akaike (1974) proposed penalizing each log likelihood to reflect the number of parameters being estimated in a particular model and then comparing them. The AIC can be defined as

$$AIC = -2(\log likelihood) + 2\,(c + p + 1)$$

where p is the number of model-specific ancillary parameters and c is the number of model covariates.

There are slight differences in the value of log-likelihood function between Weibull and Generalized Gamma models, normally in favour of the latter. However, following the AIC the best model is the Weibull in the majority of cases[17].

Fortunately, both models are nested. The estimate of one of the ancillary parameters $\hat{\kappa}$ for Generalized Gamma distribution (with standard deviation), allows to reject the Wald test of the hypothesis that $\kappa = 0$ (test for the appropriateness of the lognormal) but $\kappa = 1$ cannot be rejected (strong support against rejecting the Weibull model)[18] when the distribution selected is the Weibull distribution.

[16] Kalbfleisch and Prentice (1980) justify the selection of a model basing on the value of the log-likelihood function.

[17] The exceptions are limited to the models of Table B2, where these models use the Generalized Gamma distribution.

[18] The density function of the Generalized Gamma distribution is

$$f(t) = \begin{cases} \dfrac{\gamma^{\gamma}}{\sigma t \sqrt{\gamma}\,\Gamma(\gamma)} \exp\left(z\sqrt{\gamma} - u\right), & \text{if } \kappa \neq 0 \\ \dfrac{1}{\sigma t \sqrt{2\pi}} \exp\left(-\dfrac{z^2}{2}\right), & \text{if } \kappa = 0 \end{cases}$$

where $\gamma = |\kappa|^{-2}$, $z = sign(\kappa)\frac{\ln(t) - \mu}{\sigma}$, $u = \gamma \exp(|\kappa|\, z)$.

Another way of verifying the fit is to calculate an empirical estimate of the cumulative hazard function based on the Kaplan-Meier survival estimates, taking the Cox-Snell residuals[19] as the time variable. If the estimated model fits the data, then the Cox-Snell residuals have a standard censored exponential distribution with hazard ratio 1. In general, figures confirm the previous election.

In spite of the methods of selecting between the Weibull and Generalized Gamma distribution, their differences in terms of estimates are small, so the effect of selection is limited.

4.2.3 Unobserved Heterogeneity

Up to now, we assume inexistence of unobserved heterogeneity. In order to study if this assumption is valid, we propose the use of frailty models or survival models with unobservable heterogeneity. Frailty is introduced as an unobservable multiplicative effect a on the hazard function such that[20]

$$h(t \mid a) = ah(t)$$

where $h(t)$ is a non-frailty hazard function, a is a random positive quantity (for purposes of model identifiability is assumed to have mean one and variance θ finite) with density function $g(a)$. For purposes of mathematical tractability, we limit the choice to one of either the Gamma distribution $G\left(\frac{1}{\theta}, \theta\right)$ or the Inverse-Gaussian distribution $IG\left(1, \frac{1}{\theta}\right)$[21].

Results indicates negligible heterogeneity in all AFT models, specially for models distinguishing among levels of treatment and gender.

[19] The Cox-Snell residuals can be derived from the expression

$$\hat{r}_{C_i} = -\log\left[\hat{R}(y_i)\right]$$

where $\hat{R}(y_i) = 1 - G\left(\frac{y_i - x_i'\hat{\beta}}{\hat{\sigma}}\right)$. $G(\cdot)$ is the distribution function of the model. The Cox-Snell residual for a subject at time t is defined as $\hat{H}(t)$, the estimated cumulative hazard function otained from the fitted model.

[20] Using this idea, Lancaster (1990) presents parameter α as the total effect of unmeasured systematic differences on the hazard function. He comments several rationalisations for a mixture model, such that 'omitted variables' and 'errors in the equation'argument.

[21] Gamma distribution G(a,b) has the density

$$g(x) = \frac{x^{a-1}e^{-\frac{x}{b}}}{\Gamma(a)b^{a}}$$

For the case of Inverse-Gaussian with parameters a and b

$$g(x) = \left(\frac{b}{2\pi x^3}\right)^{\frac{1}{2}} \exp\left\{-\frac{b}{2a}\left(\frac{x}{a} - 2 + \frac{a}{x}\right)\right\}$$

4.3 PH models

Although Lancaster (1990) does not find any economic principle justifying hazard functions should be proportional, Proportional Hazard rate model (PH models) is used in a multitude of studies.

In AFT models, distribution function is assumed known, except for a few scalar parameters. The proportional hazard model, however, is non-parametric in the sense that it involves an unspecified function in the form of an arbitrary baseline hazard function. In consequence, this model is more flexible, but different approaches are required.

Let $h(t,x)$ be the hazard function of an individual with a vector of measured covariates x at time t. The proportional hazard model proposed by Cox (1972) is specified by the hazard relationship

$$h(t,x) = h_0(t) \cdot e^{x'b} \tag{3}$$

where $h_0(t)$ is an arbitrary and unspecified baseline hazard function. In this setting, covariates included in x act multiplicatively in the hazard function, unlike AFT models. This model provides estimates of the vector b, but provides no direct estimate of $h_0(t)$. Therefore, it is complicate to compare hazard functions of Cox and AFT models.

The most important assumption of the Cox proportional hazards model is that the hazard ratio is proportional over time. Once the models are estimated proportional hazards assumption is evaluated, using a test of proportional hazards based on the generalization by Grambsch and Therneau (1994). The null hypothesis of a zero slope in a generalized linear regression of the scaled Schoenfeld residuals[22] on functions of time. The null hypothesis is accepted in all models, specially when models with a more specific subsample are considered.

4.3.1 Application to data

The models estimated are defined as

$$\begin{aligned} h(t,f,x) &= h_0(t) \cdot \exp[x'b + af] \\ h_i(t_i,f_i,x_i) &= h_{0i}(t_i) \cdot \exp[x_i'b_i + a_i f_i] \quad \text{for course } i = 1,2,3,4 \end{aligned}$$

[22] The Schoenfeld residual for an individual i and a covariate k consists of the difference between the value of this covariate for individual i and its estimated expected value conditional on the hazard group when i fails (R_i):

$$\hat{r}_{ik} = X_{ik} - \hat{E}(X_{ik} \mid R_i)$$

More information in Schoenfeld (1982).

where definition of each term coincides with description of AFT model.

The PH model assumes that the hazard function is continuous and thus that there are no tied survival times. However tied events do occur in survival data. In order to solve this problem, Efron method is used. It assigns the same probability of failure to observations that fail at the same time inside the subset of risk observations.

The criterion of elimination of variables is similar to AFT models, so $levestu0$, $group0$, $benefit0$ and Madrid ($prov28$) among others are eliminated to avoid collinearity. Estimates appear in the Appendix C.

Although the sign is the opposite to the estimations of the AFT models, the conclusions are similar to the previous models. There exist a coincidence of significant estimates and a positive estimate implies an increase of the hazard rate to a job. In the case of the PH model using all the sample, the treatment increases the hazard rate to a job at 15% when women are compared with men.

5 Conclusions and extensions

The objective of this work lies in the study and evaluation of one of the active labour market policies done in Spain: the National Plan of Training and Professional Insertion, carried out by INEM or the region with the corresponding competence. We use a subsample of people who did courses in the …rst quarter of 2000 (treatment group) and other without doing these courses (control group).

Conclusions from estimates of AFT and PH models are common in this experiment:

- With respect to courses, they are more useful to reduce the duration of unemployment whether individual is a woman, specially courses 2 (Occupation) and 3 (Specialization) when they are combined with people receiving bene…ts.
- There exists a clear positive relationship between the increase of the number of years and the days of active labour demand, and the increase of the period to be unemployed.
- However the condition of being disabled (for women), the level of education and the economic activity of the job each individual would like as …rst option are not factors a¤ecting clearly the duration of an individual in unemployment.

From these conclusions, we will try to introduce the e¤ect of (unobserved) heterogeneity in parametric and semi-parametric models, using Mixed Proportional Hazards models (MPH models) and competing risk models to study the di¤erences of contracts an individual can obtain.

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Appendix A: Variable descriptions.

In order to distinguish between original variables and transformed ones, we used the letter X. For example, $levestu$ is an original variable that takes values between 0 and 9, and $levestuX$ is a transformed dummy variable that takes value one if $levestu = X$ and cero otherwise.

1. $woman$ is a dummy variable equals 1 if female.
2. age is a variable which takes values from 16 to 60 years old.
3. $levestuX$ is a group of dummy variables that adopts value one if the level of studies of the individual is X, where X may be:

$$X = \begin{cases} 0 \rightarrow & \text{Without education} \\ 1 \rightarrow & \text{Pre-Primary education without certificate} \\ 2 \rightarrow & \text{Pre-Primary education with certificate} \\ 3 \rightarrow & \text{Vocational Training 1 (FP1)} \\ 4 \rightarrow & \text{Primary education} \\ 5 \rightarrow & \text{Vocational Training 2 (FP2)} \\ 6 \rightarrow & \text{Secondary education} \\ 7 \rightarrow & \text{Other qualifications of FP} \\ 8 \rightarrow & \text{Bachelor (3 years)} \\ 9 \rightarrow & \text{Bachelor (more than 3 years)} \end{cases}$$

4. $disabled$ is a dummy variable with value 1 if the individual is disabled.
5. $benefitX$ is a set of dummy variables indicating if an individual has some benefit. X indicates which kind of benefit may be:

$$X = \begin{cases} \text{0 if the individual does not receive any help} \\ \text{63 if the individual receives benefits} \\ \text{64 if the individual receives any subsidy except for higher than 52 years and agriculture} \\ \text{65 if the individual receives a subsidy for people higher than 52 years} \\ \text{66 if the help has been disappeared by any reason} \end{cases}$$

6. $treatment$ is a dummy variable equals to 1 if the individual did a training course in the first quarter of year 2000.
7. $provX$ is a set of dummy variables indicating in which province the individual lives. The value of X appears in the table in the last part of this Appendix.
8. $groupX$ is a set of dummy variables considering different economic activities in which people desire to work as their first preference. These variables follow the ten Big Groups of the National Classification of Occupations (CNO-94):

$$X = \begin{cases} 0 \to & \text{Armed Forces} \\ 1 \to & \text{Management and Public Administrations} \\ 2 \to & \text{Technicians, professionals, scientists and intellectuals} \\ 3 \to & \text{Support technicians and professionals} \\ 4 \to & \text{White-collar workers} \\ 5 \to & \text{Restaurant workers, protection and sellers} \\ 6 \to & \text{Skilled workers in farming and fishing} \\ 7 \to & \text{Workers in factory industry, construction and mining} \\ 8 \to & \text{Operators of installations and machinery, and assemblers} \\ 9 \to & \text{Non-skilled workers} \end{cases}$$

9. $ddays$ defines the number of days that each individual has maintained his active labour demand continuously.

Index of provinces:

Alava	1	León	24
Albacete	2	Lérida	25
Alicante	3	Lugo	27
Almería	4	Madrid	28
Asturias	33	Málaga	29
Avila	5	Melilla	52
Badajoz	6	Murcia	30
Baleares	7	Navarra	31
Barcelona	8	Ourense	32
Burgos	9	Palencia	34
Cáceres	10	Las Palmas	35
Cádiz	11	Pontevedra	36
Cantabria	39	La Rioja	26
Castellón	12	Salamanca	37
Ceuta	51	S. C. Tenerife	38
Ciudad Real	13	Segovia	40
Cordoba	14	Sevilla	41
Coruña	15	Soria	42
Cuenca	16	Tarragona	43
Gerona	17	Teruel	44
Granada	18	Toledo	45
Guadalajara	19	Valencia	46
Guipuzcoa	20	Valladolid	47
Huelva	21	Vizcaya	48
Huesca	22	Zamora	49
Jaen	23	Zaragoza	50

Figure A1: Spanish provinces

Appendix B: Tables of estimates of AFT models.

TABLE B1: General AFT models

	Total	Men	Women
woman	-.118		
	(1.7)		
age	.014¤	-.015	.025¤¤
	(.008)	(.012)	(.012)
age2	.0002¤	.0006¤¤¤	.0002
	(.0001)	(.0002)	(.0002)
treatment	.456	-2.531	.192
	(.329)	(1.825)	(.597)
treatment x woman	-.162¤¤¤		
	(.046)		
ddays	.005¤¤¤	.004¤¤¤	.005¤¤¤
	(.00009)	(.0001)	(.0001)
ddays2	-1.89e-06¤¤¤	-1.62e-06¤¤¤	-2.09e-06¤¤¤
	(6.51e-08)	(1.09e-07)	(8.13e-08)
disabled	-.057	2.414¤	-1.488
	(.969)	(1.237)	(1.275)
bene...t63	-3.123	-5.304¤¤	-.974
	(1.911)	(2.278)	(1.03)
bene...t64	-.288	-.464	-.317
	(.388)	(.894)	(.684)
bene...t65	1.744	1.659	.507
	(1.234)	(1.26)	(1.071)
bene...t66	.311	1.018	-1.675¤¤
	(.499)	(.727)	(.837)
bene...t63 x woman	-.056		
	(.059)		
bene...t64 x woman	-.022		
	(.082)		
bene...t65 x woman	-.055		
	(.576)		
bene...t66 x woman	-.259¤¤¤		
	(.079)		
treatment x bene...t63	-.302¤¤¤	-.325¤¤¤	-.247¤¤¤
	(.061)	(.086)	(.087)
treatment x bene...t64	-.211¤¤	-.021	-.347¤¤¤
	(.084)	(.137)	(.108)
treatment x bene...t65	.374	.429	.094
	(.38)	(.412)	(1.136)
treatment x bene...t66	-.066	.065	-.174
	(.08)	(.12)	(.109)
Sample	19941	7836	12105

TABLE B2: AFT models for men and several levels of training

MEN	course 1	course 2	course 3	course 4
age	-.011	-.016	-.014	-.008
	(.013)	(.012)	(.013)	(.013)
age2	.0004¤¤	.0006¤¤¤	.0005¤¤¤	.0004¤¤
	(.0002)	(.0002)	(.0002)	(.0002)
treatment	-.273	-2.339	.327	-.02
	(1.154)	(1.902)	(1.183)	(.608)
ddays	.005¤¤¤	.004¤¤¤	.005¤¤¤	.005¤¤¤
	(.0002)	(.0002)	(.0002)	(.0002)
ddays2	-1.94e-06¤¤¤	-1.72e-06¤¤¤	-1.84e-06¤¤¤	-1.88e-06¤¤¤
	(1.25e-07)	(1.16e-07)	(1.20e-07)	(1.20e-07)
disabled	2.076¤	2.48¤¤	1.396¤	2.567¤
	(1.159)	(1.249)	(.846)	(1.337)
bene…t63	-.124	-.294	-.369	-.379
	(.588)	(.585)	(.556)	(.514)
bene…t64	-.216	.169	.363	.265
	(.847)	(1.258)	(.696)	(1.184)
bene…t65	.96	1.42	.815	1.141
	(1.383)	(1.28)	(1.317)	(1.318)
bene…t66	-.901	1.392¤	-.867	.981
	(.571)	(.745)	(.571)	(.687)
treatment x bene…t63	-2.758¤	-.306¤¤¤	-.522¤¤¤	-.078
	(1.618)	(.098)	(.156)	(.225)
treatment x bene…t64		.103	-.301	.104
		(.159)	(.236)	(.37)
treatment x bene…t65		.662	-.355	.449
		(.503)	(.634)	(1.193)
treatment x bene…t66		.034	.206	-.137
		(.139)	(.219)	(.264)
Sample	5136	6990	5648	5458

¤ ¤ ¤ 99% signi…cant level ¤¤ 95% signi…cant level ¤ 90% signi…cant level , standard deviations in parenthesis.

TABLE B3: AFT models for women and several levels of training

WOMEN	course 1	course 2	course 3	course 4
age	.027¤	.027¤¤	.026¤	.026¤
	(.014)	(.013)	(.014)	(.014)
age2	.00002	.0001	.00008	.00004
	(.0002)	(.0002)	(.0002)	(.0002)
treatment	.566	.286	.143	-.223
	(1.145)	(.741)	(.93)	(1.19)
ddays	.005¤¤¤	.005¤¤¤	.005¤¤¤	.005¤¤¤
	(.0002)	(.0001)	(.0001)	(.0002)
ddays2	-2.29e-06¤¤¤	-2.19e-06¤¤¤	-2.20e-06¤¤¤	-2.22e-06¤¤¤
	(1.10e-07)	(8.93e-08)	(1.02e-07)	(1.07e-07)
disabled	-1.458	-1.645	-.051	-1.838
	(1.248)	(1.287)	(1.197)	(1.254)
bene…t63	1.308	.44	-.044	1.16
	(1.188)	(1.03)	(1.101)	(1.186)
bene…t64	-.339	-.597	-.495	-.357
	(.645)	(.532)	(.574)	(.645)
bene…t65	.433	1.08	.885	.049
	(1.152)	(1.217)	(1.152)	(.876)
bene…t66	-1.481¤	-1.56¤	-1.547¤	-1.509¤
	(.884)	(.819)	(.903)	(.878)
treatment x bene…t63		-.261¤¤¤	-.233¤	-.154
		(.1)	(.124)	(.188)
treatment x bene…t64		-.293¤¤	-.409¤¤¤	-.501
		(.125)	(.145)	(.316)
treatment x bene…t65				-1.717
				(1.052)
treatment x bene…t66		-.215¤	.058	-.229
		(.117)	(.18)	(.286)
Sample	7300	10316	8629	7736

¤¤¤ 99% signi…cant level ¤¤ 95% signi…cant level ¤ 90% signi…cant level , standard deviations in parenthesis.

Appendix C: Tables of estimates of PH models.

TABLE C1: General PH models

	Total	men	women
woman	.098 (1.419)		
age	-.012¤ (.007)	.013 (.009)	-.02¤¤ (.01)
age2	-.00018¤ (.0001)	-.0004¤¤¤ (.0001)	-.0001 (.0002)
treatment	-.387 (.273)	2.015 (1.464)	-.177 (.505)
treatment x woman	.136¤¤¤ (.038)		
ddays	-.003¤¤¤ (.00007)	-.003¤¤¤ (.0001)	-.003¤¤¤ (.0001)
ddays2	1.59e-06¤¤¤ (5.37e-08)	1.35e-06¤¤¤ (8.93e-08)	1.77e-06¤¤¤ (6.79e-08)
disabled	.061 (.804)	-2.004¤¤ (1.018)	1.268 (1.079)
bene...t63	2.394 (1.56)	4.055¤¤ (1.851)	.803 (.869)
bene...t64	.239 (.323)	.391 (.736)	.273 (.58)
bene...t65	-1.457 (1.027)	-1.382 (1.039)	-.428 (.905)
bene...t66	-.257 (.415)	-.847 (.598)	1.436¤¤ (.706)
bene...t63 x woman	.048 (.05)		
bene...t64 x woman	.019 (.068)		
bene...t65 x woman	.044 (.479)		
bene...t66 x woman	.217¤¤¤ (.066)		
treatment x bene...t63	.252¤¤¤ (.05)	.27¤¤¤ (.071)	.21¤¤¤ (.073)
treatment x bene...t64	.18¤¤ (.07)	.017 (.113)	.302¤¤¤ (.091)
treatment x bene...t65	-.317 (.316)	-.358 (.339)	-.08 (.96)
treatment x bene...t66	.053 (.066)	-.05 (.099)	.142 (.092)
Sample	19941	7836	12105

TABLE C2: PH models for men and several levels of training

MEN	course 1	course 2	course 3	course 4
age	.01 (.012)	.014 (.01)	.013 (.011)	.007 (.011)
age2	-.0003¤¤ (.0002)	-.0004¤¤¤ (.0001)	-.0003¤¤¤ (.0002)	-.0002¤¤ (.0002)
treatment	.212 (1.011)	1.821 (1.504)	-.33 (1.032)	.02 (.534)
ddays	-.003¤¤¤ (.0001)	-.003¤¤¤ (.0001)	-.003¤¤¤ (.0001)	-.003¤¤¤ (.0001)
ddays2	1.71e-06¤¤¤ (1.09e-07)	1.42e-06¤¤¤ (9.45e-08)	1.62e-06¤¤¤ (1.05e-07)	1.66e-06¤¤¤ (1.05e-07)
disabled	-1.833¤ (1.015)	-2.052¤¤ (1.022)	-1.241¤ (.739)	-2.265¤ (1.172)
bene…t63	.106 (.517)	.242 (.479)	.316 (.487)	.341 (.452)
bene…t64	.217 (.743)	.113 (1.031)	.306 (.609)	.215 (1.039)
bene…t65	-.796 (1.194)	-1.178 (1.049)	-.685 (1.14)	-.969 (1.146)
bene…t66	.769 (.499)	-1.146¤ (.609)	.744 (.498)	-.869 (.603)
treatment x bene…t63	2.062 (1.419)	.252¤¤¤ (.081)	.46¤¤¤ (.137)	.068 (.197)
treatment x bene…t64		-.087 (.13)	.27 (.206)	-.101 (.326)
treatment x bene…t65		-.552 (.412)	.309 (.554)	-.402 (1.048)
treatment x bene…t66		-.028 (.114)	-.177 (.191)	.125 (.231)
Sample	5136	6990	5648	5458

¤ ¤ ¤ 99% signi…cant level ¤¤ 95% signi…cant level ¤ 90% signi…cant level , standard deviations in parenthesis.

TABLE C3: PH models for women and several levels of training

WOMEN	course 1	course 2	course 3	course 4
age	-.025¤¤ (.013)	-.023¤¤ (.011)	-.022¤ (.012)	-.025¤¤ (.013)
age2	-6.06e-07 (.0002)	-.00009 (.0002)	-.00006 (.0002)	-9.01e-06 (.0002)
treatment	-.464 (1.018)	-.235 (.621)	-.143 (.839)	.179 (1.076)
ddays	-.004¤¤¤ (.0001)	-.003¤¤¤ (.0001)	-.004¤¤¤ (.0001)	-.004¤¤¤ (.0001)
ddays2	2.17e-06¤¤¤ (9.35e-08)	1.89e-06¤¤¤ (7.24e-08)	1.98e-06¤¤¤ (8.64e-08)	2.12e-06¤¤¤ (9.09e-08)
disabled	1.431 (1.103)	1.443 (1.08)	.077 (1.049)	1.747 (1.107)
bene…t63	-1.299 (1.119)	-.358 (.883)	.047 (.981)	-1.152 (1.129)
bene…t64	.292 (.59)	.525 (.462)	.464 (.518)	.309 (.591)
bene…t65	-.405 (1.011)	-.886 (1.005)	-.786 (1.007)	-.072 (.787)
bene…t66	1.355¤ (.809)	1.336¤ (.695)	1.39¤ (.801)	1.39¤ (.807)
treatment x bene…t63		.226¤¤¤ (.087)	.209¤ (.112)	.139 (.181)
treatment x bene…t64		.255¤¤ (.108)	.373¤¤¤ (.131)	.463 (.301)
treatment x bene…t65				1.569 (.954)
treatment x bene…t66		.187¤ (.1)	-.043 (.161)	.198 (.271)
Sample	7300	10316	8629	7736

¤ ¤ ¤ 99% signi…cant level ¤¤ 95% signi…cant level ¤ 90% signi…cant level , standard deviations in parenthesis.