# Hazard Analyses of (Un)employment in Barcelona<sup>\*</sup>

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#### Abstract

Using information on the life careers of a sample of unemployed from the city of Barcelona we show that employers' and individuals' characteristics, as well as changes in the legal setting and macroeconomic conditions, all affect the probabilities of leaving and joining unemployment. Also, comparative analyses indicate that the determinants of urban (un)employment duration differ, sometimes considerably, from those typically found at the country level. This suggests that urban (un)employment may deserve a specific treatment, both in terms of economic policies and econometric specifications.

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## 1 Introduction

Urban (un)employment is an important economic and policy concern in most developed countries (Crampton 1999a). First, a substantial percentage of the population and hence of the (un)employed lives in cities. Second, metropolitan areas all around the world share many structural problems such as, for example, those related to commuting and spatial mismatch. Third, empirical evidence shows that urbanisation economies impinge upon (un)employment. Fourth, most big cities broadly define a local labour market area.

Given the relevance of this topic, it is surprising how little attention has been paid to the duration of urban (un)employment. Despite the extensive theoretical and empirical literature on urban (un)employment, studies that examine the duration of (un)employment in an (European) urban area, as it is the purpose of this paper, are scarce. To our knowledge, we can only mention the work of Fu *et al.* (1993), who estimate the distribution of unemployment spells in Shanghai using a Gaussian kernel estimator, and that of Rogers (1997), who resorts to competing risks models to discuss aspects of the spatial mismatch hypothesis in the municipalities of the Pittsburgh Metropolitan Area.

In this paper we aim to fill this gap in the literature by analysing the incidence of individual, firm, regulatory and macroeconomic factors on the likelihoods of living and joining employment in the city of Barcelona during the post-democracy period. In particular, our data come from a random sample of individuals from the city of Barcelona that signed a contract in 1989. Available information on these 1041 subjects includes age and gender. Also, for each employment contract that the individual signed prior to  $31^{st}$ December 1994, we know its duration and the job category (which, when available, we use as a proxy for education), and, for the subsequent period of unemployment, we know whether s/he received unemployment benefits and for how long. In addition, for some employers we were able to obtain its location, the number of employees and the sector of activity. As for the regulatory framework, the period of analysis covers two major legal reforms in the Spanish labour market (the Workers Statute of 1980 and the reform of 1984) and some minor reforms (notably the changes in the unemployment benefits program in 1992). Lastly, we use regional gross added value rates and provincial unemployment level and rates to control for the evolution of macroeconomic factors during the 1980s and early 1990s.

To our knowledge, the only Spanish study using a comparable employee–employer dataset is Alba-Ramírez *et al.* (2007). However, they concentrate on the analysis of Spanish unemployment between 1999 and 2002 using a competing risks specification. This

makes difficult to address the question of whether the duration of urban (un)employment has features that differ from those of the whole country. In an attempt to circumvent this limitation, we did our best to replicate the estimation results from García-Perez (1997). Since he uses administrative data and a discrete-time model analogous to the ones we will be using here (see e.g. Jenkins 1995), this comparative analysis may provide a rough intuition of how different is Barcelona's (un)employment duration from the typical Spanish pattern.

The rest of the paper is set out as follows. In Section 2 we describe the institutional setting. We first briefly review the changes in the legal setting during the period of analysis and later discuss the distinctive characteristics of urban labour markets such as that of Barcelona. In Section 3 we describe the sample and the (un)employment spells. In Section 4 we present the econometric model and analyse the empirical results. In the last section we summarise the main conclusions.

# 2 Institutional Setting

## 2.1 Legal reforms in Spain

According to Crampton (1999b), the national idiosyncrasy is a factor of the utmost importance to understand European urban unemployment. It is thus natural to start our analysis by looking at the regulatory framework of the Spanish labour market, which has changed considerably since the establishment of democracy. Notably, the Workers Statute of 1980 and the 1984–reform brought about major restructurings in the institutional setting of the 1980s and early 1990s.

Admittedly, there has been other changes in the regulation of the Spanish labour market since 1978. However, they are either too specific to deserve treatment here (e.g., in the empirical analysis we consider the effects of the Law 22/1992, but this basically modified the system of unemployment benefits) or beyond the scope of our observation period (e.g., the profound reforms carried out in 1994 and 1997). It is also important to bear in mind that our goal in briefly describing these reforms is to draw insights for the empirical analysis. Thus, we are mostly interested in their impact on the conditions of entry and exit in the labour market. Consequently, we will merely present the types of contracts that were made available to the agents by each reform and point out the main effects of the reforms on the firing costs. The interested reader is referred to Bentolila and Blanchard (1990), Bentolila and Dolado (1994) and Ferreiro and Serrano (2001) for more

details on this institutional setting.

#### 2.1.1 The Workers Statute of 1980

"Under Franco, (...) only full-time and permanent jobs could be created, dismissal procedures were very cumbersome, collective firings had to be approved by the government and severance pay was very high" (Bentolila and Blanchard, 1990: 254). Stemming from this background, the Workers Statute of 1980 (*Estatuto de los Trabajadores*, ET hereafter) sought to apply two guiding principles to the Spanish labour market. First, the output of a collective bargaining was considered an alternative institutional mechanism to regulation. This meant that agreements between employers' associations and trade unions (*convenios colectivos*) were efficient *erga omnes*. Second, the stability of the job site as the cornerstone of the system of rights created by the ET. Temporary hiring was admitted, yet under very specific circumstances such as for example sudden increases in demand.

The first principle has been broadly maintained to date, whereas the second, the socalled "causation principle", was practically abandoned after the reform of 1984. The main goal of the causation principle was to achieve a direct correspondence between the duration of the job and the type of employment contract. Accordingly, the ET only acknowledged permanent (i.e. indefinite) or temporary (i.e. fixed-term) contracts. As for the firing conditions, the ET distinguished between individual dismissals subject to the contractual obligations and collective layoffs resulting of an employer–employees agreement with prior administrative authorisation (and, in exceptional cases, direct administrative intervention).

Unfortunately, the Spanish unemployment rate showed an upward trend since the late 1970's that the ET could not break up. In fact, this legal framework was soon to be seen as too rigid with respect to the firing and hiring conditions. It was argued that it hampered employment creation and discouraged long-term contracts. In short, the ET did not succeed and, as a result, in 1984 the government launched new regulations intended to introduce more flexibility in the system. The rate of unemployment in those days was above 20% and this was explicitly mentioned in the preface of the new legal framework as the main argument for an updating of the ET barely four years after its enactment.

#### 2.1.2 The 1984 reform

The main goal of the 1984–reform was the design of new temporary contracts to foster job creation. Fourteen fixed–term contracts were defined, many of which could be used in practise for jobs of permanent nature. Entry into the labour market could be achieved by means of i) contracts linked to the so-called "measures to foster employment" (*medidas de fomento al empleo*) and ii) contracts aside the measures to foster employment (more commonly known as "ordinary contracts"). The "measures to foster employment" included, essentially, temporary and part-time contracts as well as some associated with training programs. As for the contracts aside the measures to foster employment, these included contracts of indefinite and limited duration. However, indefinite contracts actually corresponded to the permanent contracts became soon the most popular. According to the decree-law *R.D. 2104* that specified its use, they could be signed to "accomplish a work or provide a service" (e.g., the construction of a building) and to adjust firm's turnover to the seasonal evolution of the economic activity (thus becoming temporary contracts to cope with peaks of production).

#### [Insert Table 1 around here]

There is little doubt that the availability of a wide range of temporary contracts meant more flexibility in the entry into the labour market. Table 1 shows some statistics for the province of Barcelona and makes this apparent —see also García–Perea and Gomez (1993) for Spanish evidence. However, the successive use of non–indefinite contracts in the same employer–employee relationship was limited to three years. After that, the new contract became permanent. Otherwise, the firm could not hire another person for that job and had to wait a year before recalling the worker. The aim was that, whenever possible, temporary contracts were eventually transformed into permanent ones.

Moreover, the reform of 1984 implied a reduction of the firing costs. In accordance with its preference for permanent contracts, the ET did not settle any severance pay for temporary workers. The reform of 1984 modified this, although the severance pay of the indefinite–duration contracts remained comparatively high. As a result, employees were usually hired every 3 or 6 months and, in many cases, this practise extended beyond the 3-years limit through legal tricks, holding structures and some other devices that distorted the *bona fide* sense of the law.

## 2.2 Urban labour markets: the case of Barcelona

We turn now attention to Barcelona's labour market. In the 1980s this city had a population of about 1.7 million people and its Metropolitan Area (AMB hereafter) of about 2.9 million —see also Table 2. The Spanish region of which Barcelona is capital, Catalonia, had a total population of about 6 million people and its economically active population was approximately 17% of that of Spain. Catalonia's GDP is approximately 20% of the GDP of Spain, whereas the GDP of the province of Barcelona is approximately 75% of the GDP of Catalonia. These aggregate figures show the relative importance of both Catalonia and Barcelona in the Spanish economy. But which are, if any, the distinctive characteristics of Barcelona's labour market?

#### [Insert Table 2 around here]

The main tenet of this paper is that urban labour markets have indeed specific characteristics.<sup>1</sup> The concentration of human activity, for example, causes certain socio-economic problems (e.g., commuting and spatial mismatch) that are less stringent outside metropolitan areas. Similarly, the relative importance of the urban areas in the spatial distribution of the population implies that the number of both unemployed and job offers is usually above the average of the country or the region. There is also evidence that urbanisation economies impinge on the rates and the duration of unemployment, that most cities define the boundaries of a local labour market area, and that the incidence of unemployment varies between i) urban and rural areas, ii) cities of different sizes and functions, and iii) inner and outer areas of cities (Crampton 1999a).

Urban areas in OECD countries have many of these features in common and Barcelona is no exception. However, there are also important differences between cities.<sup>2</sup> In particular, the high rates of unemployment in the European ones seem to be related to the tertiarisation of economic activity, which is acting in practise as a mismatch mechanism (Crampton 1999b). Once again, Barcelona is a good example of this deindustrialisation process. According to Rojo (1999), in the 1990s about 70% of the jobs in this city were related to traditional services and, increasingly, new emerging activities. Delocation or decentralisation is another important trend in European cities (Symes 1995), especially those of southern Europe (Cheshire 1995). Trullén (1989) shows indeed that the importance of the industrial concerns in Barcelona continuously declined in the period 1970 to 1985. However, the AMB showed the opposite trend in the same period.

<sup>&</sup>lt;sup>1</sup>A similar claim lies behind the empirical studies of Elliott and Theodissiou (1992), Alperovich (1993), Fu *et al.* (1993) and Rogers (1997).

<sup>&</sup>lt;sup>2</sup>In a survey of theoretical studies, Zenou (2000) concludes that the causes of the observed differences are numerous. Among others, he refers explicitly to moral hazard problems and wage rigidities, demand shocks, frictions in the labour market and spatial mismatch.

But do commuting, tersiarisation, delocation and so on make Barcelona's labour market essentially different from the Spanish one? If so, in which sense? As an illustration, let us consider the effects of the above mentioned changes in the legal framework governing labour contracts. As shown in Table 1, temporality appears to be high in Barcelona. In fact, if we compare figures in Table 1 with the aggregates for Spain (see, e.g., Table 1 in García–Perea and Gomez 1993), we will notice that the use of temporary contracts is actually more frequent in Barcelona. On the other hand, the percentage of limited– duration contracts in the whole country is higher than in Barcelona, specially in the case of those employed for the accomplishment of a work or service. There are no important differences, however, in the number of indefinite contracts, which is small but similar in Spain and Barcelona.

In Table 2 we further present statistics for Spain, Catalonia and Barcelona regarding population, unemployed and economically active population. They show that the labour markets of Barcelona and Catalonia behave very closely and their general trends are similar to that of Spain. However, there are also differences. They arise, for example, in the rate of activity (economically active population over *de facto* population of 16 years and over), which is notably higher in Barcelona and Catalonia than in Spain because of the higher female rate of activity. Moreover, the unemployment rate (unemployed population over economically active population) during the early 1980's and part of the late 1980's was higher in Barcelona, and even higher than in Spain. On the other hand, since the late 1980's Barcelona, and even more Catalonia, had a lower unemployment rate than Spain. This seems to be mostly due to the decreasing trend of the unemployed population in both Barcelona and Catalonia.

From these remarks it is tempting to infer some relationship between the extensive use of temporary contracts in Barcelona and its low unemployment rates. However, such an assessment would be flawed because it clearly lacks of a solid statistical support. In any case, these simple comparative analyses suggest that there are certain particularities of Barcelona's labour market worth considering. In the remainder of the paper we aim to provide further insights on this claim by analysing which factors determine the probability of leaving (un)employment in Barcelona. Moreover, we will compare the importance of these factors with those found to be relevant in Spain.

# 3 Descriptive analysis

## 3.1 The sample

The individuals analysed in this study contacted one of the National Employment institute (INEM) offices in the city of Barcelona during 1989 with the aim of registering an employment contract.<sup>3</sup> From this population, we selected 1041 subjects whose National Identity Card (*Documento Nacional de Identidad*) ended in 25. Thus, by construction the sample is likely to underestimate the weight of long term contracts and overestimate the initial steps of the professional careers. At the same time, however, the sampling procedure largely guarantees that the selected group of individuals provide a representative snapshot of Barcelona's local labour market area (LLMA).<sup>4</sup>

Information on the life careers of these randomly selected individuals up to 31<sup>st</sup> December 1994 was obtained from the Social Security reports used by the INEM to compute insurance and assistance unemployment benefits —see e.g. Cebrián *et al.* (1996) for a detailed description of this statistical source. Data included basic features of the contracts signed by the individual (beginning and end dates, severance cause, job category and an identification code for the employee) as well as personal characteristics (born date and gender). Moreover, for each unemployment period that followed a contract we know whether s/he enjoyed insurance and/or assistance benefits.<sup>5</sup> Lastly, the identification code of the employee allowed us to know its location (provincial postal code) and, by crossing this code with information from the 1985 Input–Output Table of Catalonia and the Trade Union Census of 1991, the number of employees in 1984 and 1991 and the sector of activity (SIC three–digit code, CNAE–74). Therefore, the resulting dataset contains the labour market history of a sample of unemployed people and basic features of both (most of)

<sup>4</sup>First, in those days there were 52 offices in the province of Barcelona, of which 14 were in the city. Second, Barcelona's LLMA was formed by 76 municipalities in 1981, 59 in 1986 and 91 in 1991, most of them belonging to the AMB (Palacio 1995). Third, during the period 1970 to 1985 the employment in the city of Barcelona was approximately 65% of the AMB's employment (Trullén *et al.* 1989).

 ${}^{5}$ We found a few cases of benefits related to temporary disability. Rather than distinguish them as a different category, we decided to include them as assistance benefits.

<sup>&</sup>lt;sup>3</sup>Information available from the INEM included personal characteristics (gender, age, marital status and education) and preferences on the job site (shift, timetable and location). Unfortunately, this information was neither compulsory (i.e. some of these variables contained gaps) nor complete (i.e. administrative records were kept only for those subjects who contacted the INEM during the period 1993 to 1996, either because they had found another job or because they were looking for a new one).

these employees and (some of) their employers.<sup>6</sup>

The sampling scheme is analogous to the inflow sample with right censoring discussed e.g. in Cameron and Trivedi (2005). In particular, notice that all histories are rightcensored at the end of 1994. However, not all individuals were active in that date. In fact, during the period of analysis some individuals left the labour market. A few did so permanently (9 contracts had death and 1 had retirement as the cause of severance), but most where only temporarily out of the market because of the military service (this affected to 59 spells of unemployment).

Deaths did not require any special treatment for our analyses, for these observations are simply not censored but fully observed. In contrast, we needed to address the cases involving retirement and military service. Thus, we dropped those (un)employment spells in which the age of the individual at exit was 55 years or more to avoid distortions associated with the end of the labour life (see also García-Pérez 1997). Also, we subtracted from the duration of the subsequent unemployment spell the duration of the military service (24 months until 1984, 12 months until 1991 and 9 months until 1994).

### 3.2 The spells

Time spend (un)employed, denoted hereafter by t, appeared in the original files used to construct our data set measured in days. However, since contracts and wages refer typically to months, (un)employment durations were transformed to discrete intervals of a month long. Moreover, we eliminated durations less or equal than a month. These probably correspond to transitions among states rather than changes of state (García-Pérez 1997, Alba-Ramírez *et al.* 2007), although we also find cases of highly temporary work such as weekend jobs (e.g. in the leisure sector) and on-duty workers (e.g. doctors and nurses). Thus, a duration of two in our data set, for example, corresponds to a spell of more than two months but less than three. Lastly, we dropped all spells starting before  $31^{th}$  December 1978. As pointed out in Section 2, including the pre-constitutional period would mean to analyse a completely different institutional setting. In addition, this constraint addresses possible concerns about the reliability of the data in that period.

It is also important to notice that, for the sake of simplicity, our empirical analyses are limited in a number of ways. First, we consider the different spells of (un)employment

<sup>&</sup>lt;sup>6</sup>Alba-Ramírez *et al.* (2007) analyse an analogous data set, but their time period is shorter and firm data comes from other sources. In any case, notice that these informations do not constitute a proper matched data set, nor enable us to analyse intra– or inter– urban labour markets.

a person may have as different observations in the data set. This means that we do not explicitly address the existence of multiple spells and treat the different spells of an individual as different single-spell individuals. Second, we do not take into account that exit from unemployment can happen voluntarily but also because the individual is fired (other causes in our data set being mergers and acquisitions, closing downs, etc.). This means that we assume that there is a single risk rather than competing risks of exit. Lastly, we focus here on the duration of the spells and do not analyse transition (probabilities) among states.

Bearing in mind these caveats (which will be addressed in future research), next we provide descriptive analyses of the spells of (un)employment. First we report the mean and median duration for groups of individuals (Table 3.A) and firms (Table 3.B). Next we report the unconditional survivor functions, distinguishing between those estimated from the spells that occurred prior to the 1984 reform (which largely correspond to those under the 1980 reform) and those from the spells that occurred after the 1984 reform. Thus, these descriptive analyses give an idea of the sample of individuals and firms under study. Also, they provide insights about the duration of (un)employment in Barcelona and the effects of the major legal reforms during our observational period.

#### [Insert Table 3.A around here]

Table 3.A shows that the typical individual in our sample is a low educated young male that is (un)employed for less than a year. As expected from the sampling scheme we use, there are no substantial differences between the typical individual that has a job and that who has not. Similarly, Table 3.B shows that the typical firm in our sample is a large concern located in the province of Barcelona that operates in the services sector. We also find similarities between the sub-samples of hiring firms given by those contracting the individual during the employment spell and after the unemployment spell. However, rather than being a result derived from the sampling scheme of individuals, this is an expected result in an urban labour market where the population of (mature) firms is almost constant.<sup>7</sup>

#### [Insert Table 3.B around here]

Table 3.A also shows that the length of the spells is on average larger for females than males. That is, women in our sample have on average longer contracts than men, but stay

<sup>&</sup>lt;sup>7</sup>In fact, this is a common assumption in the theoretical literature of urban unemployment (see e.g. Zenou 2000).

on average more time unemployed. Moreover, people in their thirties and early forties enjoy on average (and in median) longer contracts than the youths, who in turn have on average longer contracts than people aged between 45 and 55. This is not the case for the unemployment spells, however, in which a negative relation between their duration and age seems to emerge. Lastly, more educated people tend to have longer/shorter periods of employment/unemployment.

From the statistics reported in Table 3.B, one may infer that the sub-sample of firms hiring the individuals during the employment spells differ in the duration of their contracts across the characteristics considered. Large firms in construction and agriculture, for example, use on average shorter contracts than small and medium-size firms in the industry and the services. It is also interesting to note the on average longer contracts of the firms located in the province of Barcelona with respect to those located outside. In contrast, the duration of the unemployment spells for the sub-sample of firms hiring after unemployment contracts are more homogeneous. Durations barely differ across size and location groups, and only services (longer spells) and agriculture (shorter spells) stand as different in the discrimination by sectors.

#### [Insert Graph1 around here]

In Graph 1 we report the unconditional survivor functions, i.e., the estimates of the probability of having completed spell durations of different lengths. These have the expected profile, in the sense that such estimate is decreasing with the time spend in (un)employment. However, the decline is more pronounced in the unemployment spells, particularly for those that were shorter and occurred prior to the 1984 reform. This means that, for spells of the same duration and conditional on being (un)employed up to that month, the probability of continuing unemployed was larger than that of continuing employed. One may also see a certain change in trend around the 36 and/or 48 months in both functions that probably correspond to indefinite contracts (employment) and people that decided to leave the labour market (unemployment).

The effects of the 1984 reform are apparent in the unemployment chart, but the employment spells do not provide such a clear cut picture. Fortunately, lifetable estimates behind Graph 1 allow to test whether the survivor functions before and after the 1984 were statistically the same. It turns out that results from a log-rank test reject the null hypothesis of equality of the survivor functions in both cases: the  $\chi^2$  test for the employment spells was 45.86, whereas the value for the unemployment spells was 1017.38, both statistically significant at the 5% level. Thus, the reform seem to have succeed in its goal of tackling unemployment by reducing the likelihood of remaining unemployed (regardless of the length of time the individual had been unemployed).<sup>8</sup> Moreover, the long rank test indicates that the reform altered the employment survivor function. However, at first sight the shape of the function looks the same before and after the 1984 reform. What is then the origin of the statistical difference? As previously pointed out, the 1984 reform critically affected employment decisions by expanding the menu of available contracts to include temporary contracts with low firing costs. This is reflected in the width of the steps of the employment survivor function after the reform of 1984, which are indicative of the use of repeated contracts of short duration (typically of 3 or 6 months).

# 4 Empirical results

## 4.1 The econometric specifications

As previously discussed, our data consist of a random sample of individuals (i = 1, ..., N) extracted from the inflow to the state of employment. In particular, all the (un)employment spells of these individuals are fully observed except those that ended after the common censoring time ( $31^{th}$  December 1994). Also, as previously discussed, time is measured in discrete intervals of a month long (t = 1, 2, 3, ...). Consequently, we require a duration model that accounts for the inflow sampling scheme, the right censoring in the duration variable and the discrete nature of the spells. We use the discrete-time model with a logistic hazard function proposed by Jenkins (1995). In particular, we allow for the two main causes of duration dependence (see e.g. Cameron and Trivedi 2005): "true" state dependence and unobserved heterogeneity.

Thus, if we denote by  $T_i$  the number of months individual *i* has been (un)employed, the conditional hazard  $h_{it}$  given covariates can be written as

$$h_{it} = h(t, W_i(t)) = Pr\{T_i = t | T_i \ge t, W_i(t)\} = F(\alpha_t + W_i(t)\beta_t),$$

where  $\alpha_t$  is the baseline hazard, F() is the logistic c.d.f. and  $W_i(t) = [X_i, Z_i(t)]$  includes fixed,  $X_i$ , and time-varying,  $Z_i(t)$ , covariates. We report estimates of this model in Tables 4 and 5.

<sup>&</sup>lt;sup>8</sup>One may argue that this result is driven by the number of long-term unemployed. However, dropping the spells longer than three years did not affect much the shape of the figures reported in Graph 1 and, more importantly, did not change the fact that the log-rank test rejects the null hypothesis of equality of the survivor functions.

#### [Insert Table 4 around here]

We start our analysis with an specification that does not address duration dependence. In particular,  $W_i(t)$  initially contains individual and macroeconomic factors described in the Appendix. Firm and regulatory factors, also described in the Appendix, are subsequently included. We report estimates of these specifications in the first three columns of Tables 4 and 5, respectively. Since most studies essentially consider individual, labour and/or macroeconomic determinants of (un)employment, in this way we can assess the bias caused by the omission of firm and regulatory variables. Notice also that we use the same individual, regulatory and macroeconomic factors to explain both the employment and the unemployment duration. However, firm and individual labour factors differ because they refer to the hiring firm (i.e. the firm in which the individual worked during the employment spell and the firm that hired him/her after the unemployment spell) and the previous spell (i.e. the previous unemployment/employment spell duration and the previous/current unemployment benefits are determinants of the current employment/unemployment spell).<sup>9</sup>

#### [Insert Table 5 around here]

Next we introduce state dependence in the model, either parametrically (by specifying  $\alpha_t$  and  $\beta_t$  as polynomials in ln(t)) or non-parametrically (by including a set of time-period dummies to specify  $\alpha_t$  and multiplying them by certain covariates to specify  $\beta_t$ ). In particular, the degree of the polynomials in the parametric specification was determined in the following way. We started with a degree one polynomial for the hazard baseline using the specification that includes all the available determinants. We then included additional terms of the polynomial in ln(t) as long as they were statistically significant (at the 5 per cent level we use throughout) and reduced the value of the Akaike Information Criterion. We proceed in this way up to the median value of the corresponding spell. It turns out that in our best specification  $\alpha_t$  contained six terms in the employment model and five terms in the unemployment model, which, as reported in Table 3, are indeed the sample median values.

We then used this specification of the baseline hazard to determine the polynomial in  $\beta_t$ . We started with a degree one in the individual, regulatory and macroeconomic

<sup>&</sup>lt;sup>9</sup>In the employment model we set to zero both the unemployment spell duration and the unemployment benefits previous to the first contract we observe. Since we have the life history of the individuals, this seems a plausible imputation. However, in the unemployment model we lose the last unemployment spell, for we do not have information about the hiring firm (recall that the last information we have about an individual corresponds to her/his last contract).

(excluding quarterly dummies) factors and subsequently added a degree two for those variables whose coefficients in ln(t) where statistically significant while dropping those terms in ln(t) that were not statistically significant. We found that these specifications, whose estimates are reported in the fourth column of Tables 4 and 5, produced the lowest AIC values among the alternative parametric functions we explored.<sup>10</sup>

We proceeded in an analogous way to non-parametrically specify the state dependence. Thus, we initially estimated a model with a set of month-dummies and all the available individual, firm, regulatory and macroeconomic factors. In particular, we considered three specifications with T = 12,24 and 36 month-dummies, which approximately identify 55 (65), 75 (83) and 86 (91) per cent of the (un)employment spells. We found that the specification with T = 36 and T = 12 month-dummies produced the lowest AIC values in the employment and unemployment model, respectively.<sup>11</sup>

Next we estimated a model with all the available determinants (see the Appendix), T = 12,24 and 36 month-dummies, and cross-products of the individual, regulatory and macroeconomic (excluding quarterly dummies) factors with the month-dummies. We then dropped those groups of 12,24 and 36 cross-products that were not jointly significant and reestimated the model. We found that whereas in the employment model none of these specifications yielded lower AIC values than the one using only thirty-six month-dummies (i.e. without cross products and dummies starting at T = 2, as discussed in foonote 11), in the unemployment model the specification using twelve dummies and the significant crossproducts yielded lower AICs values than any of the other non-parametric specifications. These specifications that yielded the lowest AIC values are reported in the fifth column of Tables 4 and 5.<sup>12</sup>

 $^{12}$ We also explored using cross-products of the month-dummies and the variables found relevant to

<sup>&</sup>lt;sup>10</sup>We assessed our initial specification of the baseline hazard by reestimating the model with one up to the number of terms found significant in ln(t). We found that all the terms were statistically significant and the AIC decreased with each additional term. We also explored a degree three polynomial in  $\beta_t$ for the variables whose terms in the degree one and/or two polynomials were statistically significant. It turned out that although these specifications had slightly higher/lower AIC values than than those obtained with the degree 2 polynomial reported in the fourth column of Tables 4 and 5, respectively, most of the coefficients in  $ln(t)^3$  were either barely or not statistically significant and many of those in  $ln(t)^2$ and ln(t) became then non-statistically significant.

<sup>&</sup>lt;sup>11</sup>There were no exits from employment at T = 1, so that in the employment model we either constructed the dummies from T = 2 or did not include the dummy for T = 1. We found that the first option produced better results in terms of AIC values. We also explored a constant duration for the first two or three periods of employment and a piece-wise specification based on the months-intervals reported in Table 3. However, these approaches resulted in much worse AIC values.

Lastly, we control for unobserved individual heterogeneity by including different intercepts for the hazard function, which hereby we denote by  $u_i$ :

$$h_{it} = F\left(\alpha_t + W_i(t)\beta_t + u_i\right).$$

Again this can be done using a parametric or a non-parametric specification, the difference being the use of a continuous or a discrete distribution to characterise the random intercepts. In the parametric case, it is typically assumed that  $u_i$  is a Gammaor Normally-distributed (independently of the covariates) random variable (Meyer 1990, Jenkins 1995). In the non-parametric case, it is assumed that the individual heterogeneity follows a discrete distribution (i.e, there are for example two different types of individuals in the sample), so that the likelihood function is a weighted sum of the contributions of each type of individual (Heckman and Singer 1984).

We use the best-fit specifications of the model with state dependence (according to the AIC) to address this issue. In the employment model this amounts to including thirty-six month-dummies and all the available individual, firm, regulatory and macroeconomic factors as covariates; in the unemployment model, this amounts to including all the available determinants, a degree five polynomial in ln(t) and cross products of ln(t) and  $ln(t)^2$  with the dummies of gender, lower-middle age, high education, insurance benefits and the 1992 reform as well as the days of insurance benefits received and the growth rate of Gross Added Value (see the Appendix for detailed definitions of these variables). In particular, we report estimates of these employment and unemployment specifications with normally distributed frailty in column six of Tables 4 and 5, respectively.<sup>13</sup>

specify  $\beta_t$  in the parametric specification, as well as a piece-wise constant hazard (with cross-products of all the available determinants and then selecting those groups jointly significant, as well as with those variables found relevant to specify  $\beta_t$  in the parametric specification) based on the months-intervals reported in Table 3 (although assuming constant duration for the first two or three periods of employment, as discussed in footnote 11). In the first case the AIC values where only slightly lower/higher than those obtained in the best specification of employment/unemployment reported in Tables 4 and 5, respectively, whereas in the second they were substantially worse.

<sup>13</sup>We tried to estimate analogous specifications using a "complementary loglog" model and either Gamma-distributed or non-parametric frailty (see e.g. Cameron and Trivedi 2005). The reason for using a cloglog model is that facilitates the construction of the likelihood function without imposing further constraints. In fact, as Jenkins (1995: 134) points out "[t]he logistic model turns out to be very similar to the complementary loglog one in most empirical applications [because] the logistic model converges to a proportional hazard model as the hazard rate becomes increasingly small, and the rate is indeed sufficiently small in most applications". Unfortunately, in these specifications the likelihood function did not easily convergence and, as a result, some of the coefficients and standard errors were not stable. In

## 4.2 Estimates

We begin our discussion of results by comparing the first three columns of Tables 4 and 5. As previously pointed out, these correspond to specifications that do not allow for duration dependence and use as covariates individual characteristics and macroeconomic conditions (first column), then add employers' characteristics (second column) and finally add regulatory factors (third column). Such comparison seeks to empirically asses to what extent omitting firm and regulatory factors may bias the coefficient estimates of the individual and macroeconomic factors.

We find that including firm and regulatory factors has an impact on employees' characteristics such as gender, education and insurance benefits. In fact, these variables not only suffer a sizeable change in the magnitude of the coefficient estimates but often in their statistical significance. Moreover, these effects are apparent in both the employment and the unemployment model. In contrast, macroeconomic covariates remain practically unaltered in the employment model and, perhaps with the exception of the unemployment rate, so do in the unemployment model. It seems therefore that although an omitted variables bias may exist, this essentially affects individual characteristics but not macroeconomic factors. It is also worth noting that much of this bias arises from the omission of firm characteristics, as reflected in the values of the AIC.

Next we consider the specifications that allow for duration dependence, either parametrically (column 4 in Tables 4 and 5) or non-parametrically (column 5 in Tables 4 and 5). It turns out that which approach one follows does not make a great difference here, since there is a high correspondence in terms of both coefficient estimates (once we take into account the cross-products of variables) and statistical significance. In fact, this correspondence largely extents to the specification that includes all the available determinants but does not allow for duration dependence (column 3 in Tables 4 and 5). However, there are substantial differences in some estimates. Notably, we would misleadingly conclude that the legal reform of 1980, and possibly that of 1984, had a positive impact on the probability of ending a contract. We would also miss the differential role of small firms and some sectorial effects in the likelihood of leaving unemployment. Ultimately, these

any case, it is worth noting that when convergence was achieved all the specifications yielded statistically significant likelihood ratio statistics regarding the frailty variable. Also, the signs and statistical significance of the coefficients were essentially the same across the specifications. Consequently, we decided to report only the estimates obtained assuming that  $u_i$  is Normal-distributed, which did not face convergence problems and in principle should be more efficient than the non-parametric case (which we found resulted in three (employment) and two (unemployment) different types of individuals in the sample).

differences result in a poorer fit of the specification without duration dependence.

Lastly, we consider the specifications that control for unobserved heterogeneity and state dependence. We proceed again with a comparative analysis, in this case between the results we obtained with and without different intercepts for the hazard function (columns 6 versus 4 and 5, respectively, in Tables 4 and 5). Differences are as expected, for the specifications without unobserved heterogeneity tend to over-/under-estimate the degree of negative/positive state dependence and to over-/under-estimate negative/positive effects of covariates (see e.g. Cameron and Trivedi 2005: 617-618). As a result, coefficients in the non-frailty model tend to be smaller in absolute values than in the frailty model. Notice also that allowing for unobserved heterogeneity and state dependence yields the best fit in Tables 4 and 5.

We conclude our discussion of the estimation results by focusing on the signs of the statistically significant coefficients (at conventional levels of significance) in the frailty model. In this respect, our main findings are the following. First, more educated people tend to be hired for longer periods and possibly leave earlier unemployment. Second, the duration of unemployment benefits and the receipt of assistance benefits harm your chances of leaving unemployment. Third, contracts are longer in the upswings of the business cycle and shorter during the downswings. Fourth, higher/lower unemployment rates result in shorter/longer contracts and unemployment periods. Fifth, there is stationality in the duration of unemployment, for contracts are generally shorter in the third and second quarters than in the first and second (there is also a hint of stationality in the third-quarter of the unemployment duration). Fifth, your contract is likely to be shorter if you either work for a large firm or your firm is located outside the province of Barcelona (compared to the contract you would have had you been hired by smaller, Barcelona-located firms). Lastly, all the major reforms of the 1980s and early 1990s had an impact in the labour market. However, whereas the 1992 reform reduced the duration of employment, the reforms of 1980 and 1984 increased the likelihood of leaving unemployment (in fact, the 1992 also did it, but mostly for long-term unemployed individuals).

However, the lack of significance of certain variables is also worth noting. First, gender, age and labour factors do not seem to affect the probability of leaving your current job. This means that there are no statistical differences in the likelihood of being fired between men and women, and between people of different ages. Also, the duration of the previous unemployment spell and the receipt and duration of unemployment benefits do not seem to make any difference when it comes to finishing your current contract. Second, gender and employer's characteristics do not seem to affect the probability of leaving unemployment.

This means that whether you are a man or woman, and how is the firm that is hiring you do not make a difference when it comes to exiting the unemployment.

## 4.3 Comparative analyses with the Spanish pattern

In this sub-section we take the study of García–Perez (1997) as a benchmark for comparing results from Barcelona with those obtained for Spain. Among the similarities with our study we can mention the period of analysis, the main data sources and the use of discrete-time hazard models. As for the differences, they essentially stem from the construction of the sample and the vector of explanatory variables.

One may see our sample as resulting from a national survey that was statistically representative for certain urban areas. That is, a sample analogous to ours could be obtained from a random sample of Spanish workers' life careers that was geographically stratified to be representative of the city of Barcelona (actually, our sample is not completely random because it was constructed conditional on having a labour contract in a particular moment of time). In contrast, studies using national surveys data typically use random samples from the whole country that may or may not be representative for specific urban areas.

In order to asses to what extent the differences between our estimates and those reported by García–Perez (1997) may be due to sampling differences it is interesting to compare our descriptive statistics (see Section 3) with those reported by him (in his Tables 1 and 2). First, employment spells are slightly longer in our sample (the median in Spain is 5), whereas unemployment spells are much shorter (the median in Spain is 5), whereas unemployment spells are much shorter (the median in Spain is 11). Second, there are more males in our sample (6 percentage points more in the employment spells and almost 10 more in the unemployment spells). Third, we have less high- and low-educated people (differences around 4-5 percentage points in each category), but similar upper-middle educated people. Fourth, there are very few differences in the distribution of people by age, most notably less youths in the sample of unemployment spells.

All in all, it seems that our initial sample is not that different from that analysed by García–Perez (1997). However, we had to make some further changes to facilitate comparisons between model coefficient estimates. First, we did not impose our correction for military service in the duration of unemployment. Second, we did not consider the first unemployment duration of young people between 16 and 29 years (a spell he did not observe in his sample). Third, we censored durations of unemployment larger than three years and a half to be consistent with his assumption that they are actually drop offs.

In addition, we modified the set of explanatory variables to closely follow his spec-

ification: i) employer characteristics and assistance benefits were not included; ii) we used Spanish GDP (Source: INE, 2000 constant prices) rather than the Gross Added Value of Catalonia; iii) we used Catalonia's unemployment level and rate (Source: EPA) rather than Barcelona's unemployment level and rate; iii) we included cross-products of education and age dummies with the 1984-Reform dummy; iv) we included a dummy to distinguish previous employment periods shorter than three years. Lastly, we used his specification of the state dependence and did not control for unobserved heterogeneity.

We report estimates of this specification of the employment and unemployment model using the modified sample in the last columns of Tables 4 and 5, respectively. Although some minor differences between both studies may still remain, these estimates provide a rough idea of what García–Perez (1997) might have obtained had he focused on Barcelona's (un)employment. They are therefore broadly comparable to the ones he obtained for Spain.

As expected, such comparison reveals that some of the determinants of the (un)employment duration in Barcelona are indeed different from those of Spain. In particular, we find that the effects of personal characteristics such as gender, age, the duration of the previous unemployment spell and the receipt of insurance benefits are hardly relevant in the employment model. In the unemployment model, however, this is less clear and applies only to age and the direct effects of education. Interestingly, results obtained using all the available determinants and controlling for state dependence and unobserved heterogeneity suggest that these differences cannot be attributed to the omission of relevant explanatory factors. Rather, they arise as a genuine effect of the local labour market.<sup>14</sup>

On the other hand, we find substantial similarities in the macroeconomic and regulatory factors. Thus, the business cycle and the 1984 reform seem to have affected in a similar way the urban and national labour markets considered. It is also interesting to note that both studies use analogous polynomial approximations to the shape of the baseline hazard, which suggests that urban and national (un)employment share a common pattern of state dependence. This means that, conditional on the covariates, the probability of leaving (un)employment at any point of the spell time is essentially the same in both geographical aggregations. What differs is how this conditional probability changes when the value of some determinants of (un)employment change.

<sup>&</sup>lt;sup>14</sup>We speculate that the higher rate of activity and use of temporary contracts (see Section 2.2) may lie behind these differences. However, the flexibility and demand of skilled workers that characterise urban labour markets are other factors worth considering (Crampton 1999a, Zenou 2000). In any case, what may cause that urban and national labour markets differ is a question that is beyond the scope of this paper.

Finally, it is fair to admit that the comparative analysis performed in this sub-section may not be completely thorough from an statistical point of view. However, it is worth noting that this empirical exercise yields quite sensible results. It also shows that the analysis of urban (un)employment may provide useful insights for policy makers.

## 5 Concluding remarks

Following recent developments in both urban and labour economics that suggest that urban (un)employment requires specific approaches, this paper analyses a European case study: Barcelona. We use data from a random sample of labour force participants and model the probability of leaving (un)employment as a discrete-time process to show that employers' and individuals' characteristics, as well as changes in the legal setting and the macroeconomic indicators over the 1980's and mid 1990's, all affect the probabilities of leaving and joining unemployment. In particular, we find that the main determinants of the employment duration are individual's education, macroeconomic conditions, firm characteristics and the 1992 reform. As for the determinants of unemployment duration, they include both employees and employers' characteristics, the unemployment rate and the legal reforms.

Comparative analyses indicate that although national and urban (un)employment may share a common baseline hazard, the duration of (un)employment in an urban area like Barcelona differs from the national pattern. Such differences seem to concentrate on personal characteristics, however, being macroeconomic and regulatory effects much alike. Moreover, they affect much more to the duration of employment than to that of the unemployment. In any case, this suggests that one should be careful in applying conclusions obtained from studies that employ national surveys to some urban areas (unless of course such studies take explicitly into account the spatial heterogeneity of the labour market).

Ultimately, urban (un)employment studies like this may provide useful insights for the design of economic policies. For example, since the current situation of Spain reminds that of the mid-1980s, both in terms of unemployment rates and an almost certain change in the legal setting that will simplify the menu of available contracts, our estimates indicate that (*ceteris paribus*) the impact of this new legal setting may be particularly important in increasing the likelihood of leaving unemployment in urban areas. However, further research is needed to confirm or deny this forecast. In this respect, possible extensions of this study include the comparison of our results with those from other urban environments both in Spain (e.g. Madrid) and in Europe (e.g. London, Paris, etc.). This is likely to

provide valuable insights on the nature of the European urban unemployment. Moreover, we should address issues such as the existence of multiple spells, competing risks and the unemployment-employment transitions.

# 6 Appendix: Definition of variables

- Employees' characteristics:
  - Gender: A dummy variable that takes value 1 for males and 0 for females.
  - Age: Based on the difference between the year in which the (un)employment episode starts and the date of birth, we define three categories: Young (age between 16 and 29, the residual category), Lower-Middle Age (age between 30 and 44) and Upper-Middle Age (age between 45 and 55).
  - Education: We use job category levels as a proxy (Cebrián et al. 1996, García-Pérez 1997, Alba-Ramírez et al. 2007). In particular, we define education in terms of four dummy variables: High Education (which takes value 1 for engineers and graduates, technical engineers and other skilled workers, and chief and department heads), Upper-Mid Education (other semi-skilled workers, skilled workers and auxiliary workers), Lower-Mid-Education (semi-skilled and skilled labourers) and Low Education (semi-skilled labourers, unskilled labourers and 16 to 18 years old workers), which is the residual category.

### <u>Labour factors</u>:

- Previous (un)employment spell. Duration in months of the previous (un)employment spell.
- Insurance Benefits. A dummy variable that takes value 1 if the individual enjoyed insurance benefits during the unemployment spell and for how long (number of days).
- Assistance Benefits. A dummy variable that takes value 1 if the individual enjoyed assistance benefits during the unemployment spell.

(Source: Social Security and INEM).

• <u>Macroeconomic Indicators</u>:

- Gross Added Value. Growth rate of the yearly Gross Added Value of Catalonia at 2000 constant prices (in thousand of Euros) in the year in which the (un)employment episode starts and with respect to the previous year.

(Source: BMORES DATABASE, Ministerio de Economía y Hacienda).

– Unemployment. Quarterly unemployment level of the province of Barcelona in the year-quarter in which the (un)employment episode starts and growth rate of this unemployment level with respect to same quarter of the previous year.

(Source: Own calculations from EPA, Institut Nacional de Estadística).

 Stationality: Quarterly dummy variables that take value 1 if the (un)employment episode started in the second, third and fourth quarter of the year, being the first quarter the residual category.

(Source: Own calculations).

- Employers' characteristics:
  - Size: Dummies for firms of different size, measured by the (upper rounded) average number of employees in 1985 and 1991. In particular, Small Size firms are those with less than 10 employees, Lower-Mid-Size firms are those with 10 to 19 employees, Upper-Mid-Size firms are those with 20 to 49 employees, and Large firms are those with more than 50 employees (the residual category).
  - Sector. We grouped the sampling mode of the three-digit SIC codes (CNAE-1974) for 1985 and 1991 into four sectors: Agriculture (SIC codes below 100), Industry (SIC codes between 100 and 500), Construction (SIC codes between 500 and 600, the residual category) and Services (SIC codes above 600).

(Source: 1985 Catalonia Input–Output Table and 1991 employers census of *Comisiones Obreras*).

 Location: A dummy variable that takes value 1 for those concerns located in the province of Barcelona and 0 otherwise.

(Source: Social Security and INEM).

• Regulatory factors:

- Reform of 1980. A dummy variable that takes value 1 if the (un)employment episode started after October 8 1980 but before August 2 1984.
- Reform of 1984. A dummy variable that takes value 1 if the (un)employment episode started after August 2 1984.

Reform of 1992. A dummy variable that takes value 1 if the (un)employment episode started after April 8 1992. We also included cross-products of this dummy with the dummies of unemployment benefits – see Cebrián *et al.* (1996).

(Source: Boletín Oficial del Estado).

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	1989	1990	1991	1992	1993	1994
Temporary	$^{8,2}$	28,2	25,2	$21,\!4$	16.8	_
Part-time	$^{8,6}$	$^{9,7}$	$10,\!6$	12	16.3	18
Training	$10,\!9$	$_{9,9}$	$^{8,7}$	$^{4,6}$	2.2	_
Practice	$^{5,7}$	$^{4,8}$	$^{4,1}$	$^{2,5}$	$^{1,2}$	1
Indefinite	$^{3,6}$	$^{4,4}$	$^{3,7}$	4	3.2	6
Economic cycle	25	$24,\!4$	$21,\!9$	24	58.2	63
Work or service	9.6	$^{0,7}$	$13,\!4$	$17,\!8$	0	0
Interim	$^{4,2}$	$^{4,3}$	$^{5,4}$	$^{6,1}$	_	_
Law $22/1992$					1.5	1
Law $10/1994$						1
Others					0.4	6

Table 1: Types of labour contracts (% of total, province of Barcelona).

Source: INEM (Barcelona).

 $\underline{\text{Note:}}$  Interim contracts correspond to temporary works in public administrations.

# Table 2: Population over 16, Unemployment Population and EconomicallyActive Population: Province of Barcelona, Catalonia and Spain (1980-1994).

	1980	1981	1982	1983	1984	1985	1986	1987	1988	1989	1990	1991	1992	1993	1994
Population															
Barcelona	$^{3,34}$	$^{3,38}$	$^{3,41}$	$^{3,44}$	$^{3,48}$	$^{3,51}$	$^{3,54}$	$^{3,59}$	$^{3,62}$	$^{3,66}$	$^{3,69}$	$^{3,72}$	$^{3,76}$	3,79	$^{3,82}$
Catalonia	$^{4,31}$	$^{4,35}$	$^{4,40}$	$^{4,44}$	$^{4,49}$	$^{4,52}$	$^{4,56}$	$^{4,62}$	$^{4,66}$	$^{4,71}$	4,78	$^{4,83}$	$^{4,88}$	$^{4,92}$	$^{4,97}$
Spain	$26,\!80$	27,16	27,52	$27,\!88$	27,24	$28,\!63$	28,95	29,36	29,84	$_{30,21}$	$_{30,45}$	30,73	31,03	$^{31,31}$	31,59
Unemployed															
Barcelona	$^{0,25}$	$^{0,32}$	$^{0,40}$	$^{0,42}$	$^{0,44}$	$^{0,45}$	$^{0,44}$	$^{0,47}$	$^{0,40}$	$^{0,31}$	$^{0,27}$	$^{0,27}$	$^{0,27}$	$^{0,45}$	$^{0,47}$
Catalonia	$^{0,28}$	$^{0,36}$	$^{0,45}$	$^{0,47}$	$^{0,49}$	$^{0,51}$	$^{0,49}$	$^{0,52}$	$^{0,43}$	$^{0,34}$	$^{0,31}$	$^{0,32}$	0,33	0,53	0,56
Spain	1,54	1,91	$^{2,18}$	$^{2,38}$	2,78	2,99	2,92	$^{2,96}$	2,90	$^{2,54}$	$^{2,45}$	2,56	$^{2,88}$	$^{3,65}$	$^{3,84}$
Active															
Barcelona	1,76	1,77	1,78	1,78	1,79	1,77	1,83	1,98	1,93	1,96	1,96	$^{2,02}$	$1,\!99$	2,07	2,08
Catalonia	$^{2,27}$	$^{2,29}$	$^{2,32}$	$^{2,31}$	$^{2,32}$	$^{2,30}$	$^{2,37}$	$^{2,54}$	2,50	2,53	2,56	$^{2,63}$	$^{2,61}$	$^{2,67}$	2,71
Spain	13,42	13,50	$13,\!68$	$13,\!88$	13,92	14,01	14,20	14,88	15,22	15,33	15,49	$15,\!68$	15,75	15,97	16, 11

Source: Survey of the Active Population (EPA), National Institute for Employment.

Note: Data (in millions) refer to the third quarter of the corresponding year.

Variables	Observations	Percentage (by Variable)	Mean Duration	Median Duration
Employment				
Less than 3 months	897	26.11	2.49	2
3 to 6 months	862	25.09	4.99	5
6 to 12 months	761	22.15	8.42	7
12 to $24$ months	503	14.64	16.79	16
24 to $36$ months	211	6.14	28.55	28
More than 36 months	201	5.85	49.00	43
Gender				
Female	1,129	33.87	11.43	6
Male	2,306	67.13	10.56	6
Age				
Young	2,214	64.45	10.78	6
Lower-Middle-Age	919	26.75	11.41	7
Upper-Middle-Age	302	8.79	9.61	6
Education				
Low-Education	1,421	41.37	9.30	6
Lower-Middle-Education	1,166	33.94	10.31	6
Upper-Middle-Education	444	12.93	12.85	7
High-Education	241	7.02	14.66	8
Uncensored Spells	3,435	100	10.85	6
Unemployment				
Less than 3 months	938	36.20	2.39	2
3 to 6 months	651	25.13	4.83	5
6 to 12 months	589	22.73	8.91	9
12 to $24$ months	217	8.38	17.64	17
24 to $36$ months	63	2.43	30.01	30
More than 36 months	77	2.97	58.71	54
Gender				
Female	779	30.07	9.20	5
Male	1,812	69.93	7.59	5
Age				
Young	$1,\!658$	63.99	8.35	5
Lower-Middle-Age	697	26.90	7.96	5
Upper-Middle-Age	235	9.07	6.53	4
Education				
Low-Education	1,133	43.73	8.39	5
Lower-Middle-Education	863	33.31	6.94	4
Upper-Middle-Education	306	11.81	8.64	5
High-Education	145	5.60	7.31	4
Uncensored Spells	2,591	100	8.07	5

Table 3.A: Descriptive Statistics (by Groups of Individuals).

	Observations	Percentage	Mean	Median
Variables	(Uncensored Employment Spells)	(by Variable)	Duration	Duration
Size	2,349			
Small	538	22.90	11.50	7
Lower-Middle-Size	310	13.20	10.68	6.5
Upper-Middle-Size	488	20.77	11.11	7
Large	1,013	43.12	10.07	6
Sector	2,603			
Agriculture	4	0.15	8	4.5
Industry	562	21.59	11.79	7
Construction	483	18.56	7.82	6
Services	1,554	59.70	11.00	6
Location	3,435			
Province of Barcelona	3,135	91.27	11.01	6
Others	300	8.73	9.85	6
others				
	Observations	Percentage	Mean	Median
Variables	Observations (Uncensored Unemployment Spells)	Percentage (by Variable)	Mean Duration	Median Duration
Variables Size	Observations (Uncensored Unemployment Spells) 1,710	Percentage (by Variable)	Mean Duration	Median Duration
Variables Size Small	Observations (Uncensored Unemployment Spells) 1,710 400	Percentage (by Variable) 23.39	Mean Duration 7.79	Median Duration 5
Variables Size Small Lower-Middle-Size	Observations (Uncensored Unemployment Spells) 1,710 400 232	Percentage (by Variable) 23.39 13.57	Mean Duration 7.79 7.61	Median Duration 5 5
Variables Size Small Lower-Middle-Size Upper-Middle-Size	Observations (Uncensored Unemployment Spells) 1,710 400 232 347	Percentage (by Variable) 23.39 13.57 20.29	Mean Duration 7.79 7.61 7.87	Median Duration 5 5 4
Variables Size Small Lower-Middle-Size Upper-Middle-Size Large	Observations (Uncensored Unemployment Spells) 1,710 400 232 347 731	Percentage (by Variable) 23.39 13.57 20.29 42.75	Mean Duration 7.79 7.61 7.87 7.62	Median Duration 5 5 4 4 4
Variables Size Small Lower-Middle-Size Upper-Middle-Size Large Sector	Observations           (Uncensored Unemployment Spells)           1,710           400           232           347           731           1,924	Percentage (by Variable) 23.39 13.57 20.29 42.75	Mean Duration 7.79 7.61 7.87 7.62	Median Duration 5 5 4 4 4
Variables Size Small Lower-Middle-Size Upper-Middle-Size Large Sector Agriculture	Observations           (Uncensored Unemployment Spells)           1,710           400           232           347           731           1,924           4	Percentage (by Variable) 23.39 13.57 20.29 42.75 0.21	Mean Duration 7.79 7.61 7.87 7.62 4.75	Median Duration 5 5 4 4 4 2.5
Variables Size Small Lower-Middle-Size Upper-Middle-Size Large Sector Agriculture Industry	Observations           (Uncensored Unemployment Spells)           1,710           400           232           347           731           1,924           4           443	Percentage (by Variable) 23.39 13.57 20.29 42.75 0.21 23.02	Mean Duration 7.79 7.61 7.87 7.62 4.75 7.38	Median Duration 5 5 4 4 4 2.5 4
Variables         Size         Small         Lower-Middle-Size         Upper-Middle-Size         Large         Sector         Agriculture         Industry         Construction	Observations           (Uncensored Unemployment Spells)           1,710           400           232           347           731           1,924           4           443           365	Percentage (by Variable) 23.39 13.57 20.29 42.75 0.21 23.02 18.97	Mean Duration 7.79 7.61 7.87 7.62 4.75 7.38 7.14	Median Duration 5 5 4 4 4 2.5 4 5
VariablesSizeSmallLower-Middle-SizeUpper-Middle-SizeLargeSectorAgricultureIndustryConstructionServices	Observations           (Uncensored Unemployment Spells)           1,710           400           232           347           731           1,924           4           443           365           1,112	Percentage (by Variable) 23.39 13.57 20.29 42.75 0.21 23.02 18.97 57.80	Mean Duration 7.79 7.61 7.87 7.62 4.75 7.38 7.14 8.10	Median Duration 5 5 4 4 4 2.5 4 5 5 5
VariablesSizeSmallLower-Middle-SizeUpper-Middle-SizeLargeSectorAgricultureIndustryConstructionServicesLocation	Observations         (Uncensored Unemployment Spells)         1,710         400         232         347         731         1,924         4         365         1,112         2,590	Percentage (by Variable) 23.39 13.57 20.29 42.75 0.21 23.02 18.97 57.80	Mean Duration 7.79 7.61 7.87 7.62 4.75 7.38 7.14 8.10	Median Duration 5 5 4 4 4 2.5 4 5 5 5
VariablesSizeSmallLower-Middle-SizeUpper-Middle-SizeLargeSectorAgricultureIndustryConstructionServicesLocationProvince of Barcelona	Observations         (Uncensored Unemployment Spells)         1,710         400         232         347         731         1,924         4         43         365         1,112         2,590         2,371	Percentage (by Variable) 23.39 13.57 20.29 42.75 0.21 23.02 18.97 57.80 91.54	Mean Duration 7.79 7.61 7.87 7.62 4.75 7.38 7.14 8.10 8.05	Median Duration 5 5 4 4 4 2.5 4 5 5 5

## Table 3.B: Descriptive Statistics (by Groups of Firms).

<u>Note</u>: There are 481 censored employment spells (12.28% of the 3,916 employment spells experienced by 1,014 individuals in 2,729 firms) and 347 censored unemployment spells (11.81% of the 2,938 unemployment spells experienced by 920 individuals exiting from unemployment to 2,188 firms).

# Table 4: Determinants of the Employment Duration.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Gender	0.1502***	0.0653	0.0578	-0.5213***	0.0126	0.0117	-0.1425
	(0.0397)	(0.0486)	(0.0488)	(0.2268)	(0.0496)	(0.0640)	(0.0939)
Lower-Middle Age	-0.1098***	-0.1230***	-0.1144***	-0.0721	-0.0698	-0.0954	0.1832
	(0.0416)	(0.0524)	(0.0528)	(0.0537)	(0.0538)	(0.0662)	(0.1262)
Upper-Middle Age	0.1364***	0.0479	0.0637	-1.8147***	0.0052	-0.0301	-0.0363
	(0.0655)	(0.0864)	(0.0868)	(0.5379)	(0.0893)	(0.1114)	(0.2272)
High Education	-0.7235***	-0.8260***	-0.8384***	-0.6984***	-0.6715***	-0.7419***	-0.6100***
	(0.0720)	(0.0874)	(0.0882)	(0.0887)	(0.0894)	(0.1061)	(0.1755)
Upper-Mid Education	-0.4329***	-0.5194***	-0.5192***	-0.4366***	-0.4274***	-0.4400***	-0.3398***
	(0.0563)	(0.0688)	(0.0693)	(0.0698)	(0.0704)	(0.0810)	(0.0554)
Lower-Mid Education	-0.0601	-0.1317***	-0.1280***	-0.7481***	-0.1236***	-0.1262***	-0.0259
	(0.0413)	(0.0514)	(0.0515)	(0.2410)	(0.0521)	(0.0612)	(0.0396)
Duration Previous Unemployment Sp	pell -0.0012	-0.0003	-0.0004	0.0001	0.0006	0.0011	-0.0011
	(0.0012)	(0.0014)	(0.0014)	(0.0015)	(0.0016)	(0.0019)	(0.0013)
Insurance Benefits	0.1169***	0.1442*	0.1173	-1.0706***	0.0431	-0.0098	-0.0173
	(0.0580)	(0.0739)	(0.0773)	(0.3839)	(0.0796)	(0.0831)	(0.0385)
Duration Insurance Benefits	-0.0003	-0.0005	-0.0005	0.0014	-0.0002	0.0001	. ,
	(0.0002)	(0.0003)	(0.0003)	(0.0013)	(0.0003)	(0.0003)	
Assistance Benefits	0.2427***	0.2928***	0.2642***	0.2313***	0.1904*	0.1810	
	(0.0851)	(0.1010)	(0.1156)	(0.1146)	(0.1154)	(0.1267)	
GAV Growth $\operatorname{Rate}^{a}$	0.0222***	0.0202	0.0299***	-0.0287	0.0338***	0.0334***	-0.1346
	(0.0102)	(0.0131)	(0.0139)	(0.0467)	(0.0150)	(0.0164)	(0.0850)
Unemployment $Rate^{b}$	0.0546***	0.0655***	0.0584***	-0.0203	0.0398***	0.0500***	0.0321***
	(0.0043)	(0.0059)	(0.0065)	(0.0288)	(0.0069)	(0.0078)	(0.0052)
Unemployment Growth $Rate^{b}$	0.0027***	0.0022	0.0077***	0.0047*	0.0048*	0.0032	0.0003
	(0.0013)	(0.0017)	(0.0025)	(0.0027)	(0.0027)	(0.0030)	(0.0013)
$2^{nd}$ Quarter	0.2309***	0.2148***	0.2292***	0.1808***	0.1523***	0.1495***	0.1388***
•	(0.0487)	(0.0603)	(0.0603)	(0.0613)	(0.0615)	(0.0689)	(0.0482)
$3^{rd}$ Quarter	0.3873***	0.4015***	0.4061***	0.3462***	0.3131***	0.3052***	0.2868***
	(0.0510)	(0.0624)	(0.0625)	(0.0632)	(0.0634)	(0.0706)	(0.0506)
4 <sup>th</sup> Quarter	0.1590***	0.1576***	0.1510***	0.1325***	0.1152*	0.1009	0.1423***
	(0.0510)	(0.0636)	(0.0639)	(0.0640)	(0.0646)	(0.0713)	(0.0493)
Small Firm	× /	-0.1867***	-0.1862***	-0.2092***	-0.2187***	-0.2230***	( )
		(0.0583)	(0.0587)	(0.0593)	(0.0593)	(0.0683)	
Lower-Mid-Size Firm		-0.0207	-0.0199	-0.0605	-0.0617	-0.0634	
		(0.0700)	(0.0702)	(0.0712)	(0.0717)	(0.0828)	
Upper-Mid-Size Firm		-0.1046*	-0.1105*	-0.1316***	-0.1350***	-0.1125	
		(0.0597)	(0.0599)	(0.0606)	(0.0605)	(0.0708)	
Agriculture		0.0130	-0.1208	-0.1453	-0.1970	-0.4254	
		(0.7380)	(0.7445)	(0.7567)	(0.7797)	(0.8136)	
Industry		-0.6135***	-0.6192***	-0.4953***	-0.4543***	-0.4519***	
		(0.0736)	(0.0744)	(0.0760)	(0.0758)	(0.0923)	
Services		-0.4167***	-0.4111***	-0.3361***	-0.3071***	-0.3212***	
		(0.0641)	(0.0646)	(0.0667)	(0.0668)	(0.0836)	
Located in Barcelona		-2.4908***	-2.5913***	-2.7348***	-2.5595***	-2.9451***	
		(0.9939)	(0.9638)	(1.3949)	(1.0185)	(1.0819)	
1980 Reform			0.4542***	0.2464	0.2180	-0.0171	
			(0.2092)	(0.2146)	(0.2222)	(0.2430)	
1984 Reform			0.4142*	0.1230	0.0452	-0.1914	0.4238***
			(0.2161)	(0.2163)	(0.2199)	(0.2368)	(0.1644)
1992 Reform			-0.3573***	0.2708	-0.4099***	-0.4586***	
			(0.1137)	(0.4115)	(0.1123)	(0.1182)	
1992 Reform $\times$ Insurance Benefits			0.1748	0.1938	0.1615	0.2210	
			(0.1442)	(0.1479)	(0.1462)	(0.1574)	
1992 Reform $\times$ Assistance Benefits			0.2001	0.1777	0.2337	0.1793	
			(0.2332)	(0.2384)	(0.2332)	(0.2577)	
			· · · · /	/	· · · · /		

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ln(t)				$13.9664^{***}$			$10.3676^{***}$
				(1.1410)			(0.4039)
$ln(t)^2$				$-17.4566^{***}$			-8.6336***
				(2.0686)			(0.6788)
$ln(t)^3$				$10.0224^{***}$			$2.9587^{***}$
				(1.7838)			(0.4480)
$ln(t)^4$				-3.0912***			$-0.4162^{***}$
				(0.7423)			(0.1257)
$ln(t)^5$				$0.4921^{***}$			0.0144
				(0.1475)			(0.0126)
$ln(t)^6$				-0.0315***			
				(0.0112)			
$\operatorname{Gender} \times ln(t)$				$0.4690^{***}$			$0.1032^{***}$
				(0.2296)			(0.0463)
$\operatorname{Gender} \times \ln(t)^2$				-0.0826			
				(0.0518)			
Lower-Middle Age $\times ln(t)$				$1.7616^{***}$			$0.1835^{***}$
				(0.5394)			(0.0705)
Lower-Middle Age $\times ln(t)^2$				-0.3574***			
				(0.1250)			
Lower-Mid Education $\times ln(t)$				$0.6136^{***}$			
				(0.2427)			
Lower-Mid Education $\times ln(t)^2$				-0.1229***			
				(0.0548)			
Insurance Benefits $\times ln(t)$				0.9928***			
				(0.3782)			
Insurance Benefits $\times ln(t)^2$				$-0.1785^{***}$			
				(0.0848)			
Duration Insurance Benefits $\times ln(t)$	)			-0.0011			
				(0.0013)			
Duration Insurance Benefits $\times ln(t)$	2			0.0001			
				(0.0003)			
1992 Reform $\times ln(t)$				-0.4313			
				(0.4964)			
1992 Reform $\times ln(t)^2$				0.0259			
				(0.1360)			
GAV Growth $\operatorname{Rate}^a \times \ln(t)$				$0.0985^{***}$			$0.1052^{***}$
				(0.0442)			(0.0435)
GAV Growth $\operatorname{Rate} \times ln(t)^2$				$-0.0288^{***}$			
				(0.0097)			
Unemployment $Rate \times ln(t)$				0.0421			
				(0.0300)			
Unemployment $\operatorname{Rate} \times \ln(t)^2$				-0.0039			
				(0.0071)			
High Education $\times ln(t)$							0.0253
							(0.0793)
1984 Reform $\times ln(t)$							-0.1230*
							(0.0736)
1984 Reform $\times {\rm Lower-Middle}$ Age							-0.0970
							(0.1327)
1984 Reform $\times {\rm Upper-Middle}$ Age							-0.0719
							(0.1994)
AIC	24958.68	16983.13	16977.42	15921.64	15463.44	15407.38	24244.25

## Table 4 (Cont): Determinants of the Employment Duration.

<u>Note</u>: Robust standard errors in brackets. \*\*\*, \*\* and \* denote 1%, 5% and 10% significance, respectively. Columns (1), (2) and (3) do not include state dependence variables. Column (4) includes a parametric function in ln(t) to allow for state dependence, whereas column (5) uses a non-parametric approach (36 unreported month-dummy variables). Column (6) controls for Normally-distributed unobserved heterogeneity using the same specification as that of Column (5). Column (7) aims to replicate the specification used by García Perez (1997) for Spain. The variable with the upper index <sup>a</sup> refers in this case to Spain rather than Catalonia, whereas variables with the upper index <sup>b</sup> refer to Catalonia rather than Barcelona.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Gender	$0.3382^{***}$	$0.1504^{***}$	0.1927***	0.3211	0.2311***	0.4094	0.3064***
	(0.0466)	(0.0696)	(0.0701)	(0.2476)	(0.0734)	(0.2604)	(0.0483)
Lower-Middle Age	-0.0153	0.1406*	0.0881	0.1107	$0.5706^{***}$	0.1394	0.0653
	(0.0500)	(0.0779)	(0.0784)	(0.2734)	(0.2184)	(0.2825)	(0.0712)
Upper-Middle Age	0.0988	$0.2852^{***}$	$0.2447^{*}$	0.3031***	0.3118***	0.3062***	$0.5298^{***}$
	(0.0783)	(0.1261)	(0.1256)	(0.1308)	(0.1314)	(0.1542)	(0.2358)
High Education	$0.1702^{*}$	0.1398	0.1007	0.8000*	0.1070	0.7868*	0.5956
	(0.0965)	(0.1467)	(0.1483)	(0.4551)	(0.1555)	(0.4640)	(0.3830)
Upper-Mid Education	-0.1218*	-0.0023	-0.0364	-0.0305	-0.0405	0.0115	-0.3067
	(0.0684)	(0.1060)	(0.1064)	(0.1102)	(0.1103)	(0.1244)	(0.2239)
Lower-Mid Education	$0.1509^{***}$	$0.1869^{***}$	$0.1393^{***}$	$0.1487^{***}$	$0.1559^{***}$	$0.1789^{***}$	$0.5662^{***}$
	(0.0483)	(0.0710)	(0.0707)	(0.0735)	(0.0733)	(0.0834)	(0.1631)
Duration Previous Employment S	pell -0.0022*	-0.0007	0.0003	0.0010	0.0000	0.0016	-0.0074***
	(0.0012)	(0.0018)	(0.0018)	(0.0020)	(0.0018)	(0.0019)	(0.0023)
Insurance Benefits	$0.3599^{***}$	0.0882	0.0437	-0.4338	$0.5187^{***}$	-0.4931	$-0.3133^{***}$
	(0.0624)	(0.0908)	(0.0921)	(0.3689)	(0.1171)	(0.3488)	(0.0564)
Duration Insurance Benefits	-0.0021***	$-0.0017^{***}$	$-0.0014^{***}$	$-0.0076^{***}$	-0.0009***	-0.0070***	
	(0.0002)	(0.0003)	(0.0003)	(0.0031)	(0.0004)	(0.0019)	
Assistance Benefits	-0.6745***	-0.3690***	-0.4325***	-0.6362***	$-0.6251^{***}$	$-0.7346^{***}$	
	(0.0678)	(0.1012)	(0.1084)	(0.1146)	(0.1131)	(0.1269)	
GAV Growth $Rate^{a}$	$0.0795^{***}$	$0.0659^{***}$	$0.0788^{***}$	0.0026	$0.0855^{***}$	0.0002	$0.1649^{***}$
	(0.0113)	(0.0147)	(0.0179)	(0.0534)	(0.0193)	(0.0520)	(0.0498)
Unemployment $Rate^{b}$	0.0366***	-0.0109*	-0.0286***	-0.0355***	-0.0362***	$-0.0415^{***}$	0.0130***
	(0.0045)	(0.0064)	(0.0087)	(0.0091)	(0.0092)	(0.0101)	(0.0059)
Unemployment Growth $\operatorname{Rate}^{b}$	-0.0033***	-0.0136***	0.0025	0.0068	0.0057	0.0068	-0.0089***
	(0.0017)	(0.0023)	(0.0040)	(0.0042)	(0.0042)	(0.0045)	(0.0017)
$2^{nd}$ Quarter	-0.0755	-0.0377	0.0164	0.0547	0.0385	0.0495	-0.0617
	(0.0635)	(0.0934)	(0.0948)	(0.0983)	(0.0987)	(0.1071)	(0.0658)
$3^{rd}$ Quarter	-0.2165***	-0.1247	-0.1086	-0.1364	-0.1575*	-0.1530	-0.1227***
	(0.0600)	(0.0862)	(0.0873)	(0.0902)	(0.0899)	(0.0992)	(0.0618)
4 <sup>th</sup> Quarter	-0.0244	-0.0274	-0.0459	-0.0643	-0.0815	-0.0388	-0.0371
	(0.0612)	(0.0881)	(0.0893)	(0.0926)	(0.0926)	(0.1020)	(0.0628)
Small Firm		-0.0614	-0.1163	-0.1570*	-0.1571*	-0.1729*	
		(0.0797)	(0.0805)	(0.0835)	(0.0835)	(0.0942)	
Lower-Mid-Size Firm		-0.0016	-0.0462	-0.1033	-0.1080	-0.1038	
		(0.0959)	(0.0967)	(0.1012)	(0.1011)	(0.1135)	
Upper-Mid-Size Firm		-0.1048	-0.0759	-0.1034	-0.0906	-0.1011	
		(0.0826)	(0.0836)	(0.0874)	(0.0876)	(0.0978)	
Agriculture		1.0044	1.3015	2.5769***	1.9920***	2.6869	
-		(1.4208)	(1.4220)	(0.9015)	(0.9028)	(1.9033)	
Industry		0.0363	0.1199	0.1752*	0.1445	0.1999*	
-		(0.0994)	(0.1004)	(0.1046)	(0.1034)	(0.1177)	
Services		-0.1103	-0.0141	-0.0186	-0.0230	-0.0339	
		(0.0856)	(0.0884)	(0.0919)	(0.0914)	(0.1053)	
Located in Barcelona		0.0018	-0.1012	-0.1571	-0.0941	0.1670	
		(1.0352)	(1.0361)	(1.0366)	(1.0345)	(1.1458)	
1980 Reform		(	1.0450***	1.4579***	1.1979***	1.5941***	
			(0.2425)	(0.2899)	(0.2878)	(0.2981)	
1984 Reform			1.6815***	2.2186***	1.8064***	2.5059***	0.4309***
-			(0.2723)	(0.3218)	(0.3427)	(0.3328)	(0.0956)
1992 Reform			0.5104***	0.1205	20.8988***	0.1336	()
			(0.1946)	(0.5014)	(0.9821)	(0.5357)	
1992 Reform X Insurance Repetit	5		-0.1010	-0.0994	-0.0603	-0.1903	
Herein A Insurance Bellent	-		(0.2218)	(0.2375)	(0.2506)	(0.2618)	
1992 Reform X Assistance Repeti	ts		0.0474	-0.0957	-0.0782	0.0065	
			(0.2891)	(0.3037)	(0.3108)	(0.3302)	
			(=	(	()	(	

# Table 5: Determinants of the Unemployment Duration.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ln(t)				8.9019***		$9.2062^{***}$	$15.3973^{***}$
				(0.8170)		(0.8253)	(0.5672)
$ln(t)^2$				-11.6151***		$-11.9473^{***}$	-16.6344 ***
				(1.1460)		(1.1574)	(0.8732)
$ln(t)^3$				$6.3781^{***}$		$6.6151^{***}$	$7.6765^{***}$
				(0.7407)		(0.7434)	(0.5627)
$ln(t)^4$				-1.5890***		$-1.6535^{***}$	-1.5831***
				(0.2045)		(0.2031)	(0.1566)
$ln(t)^5$				$0.1457^{***}$		$0.1516^{***}$	$0.1169^{***}$
				(0.0199)		(0.0196)	(0.0156)
$\operatorname{Gender} \times ln(t)$				-0.3108		-0.3959	
				(0.2834)		(0.2888)	
$\operatorname{Gender} \times \ln(t)^2$				$0.1353^{*}$		$0.1544^{***}$	
				(0.0729)		(0.0731)	
Lower-Middle Age $\times ln(t)$				-0.2594		-0.3163	
				(0.3213)		(0.3323)	
Lower-Middle Age $\times ln(t)^2$				0.1227		0.1319	
				(0.0867)		(0.0908)	
High Education $\times ln(t)$				-0.4508		-0.3097	-0.1532
				(0.5591)		(0.5442)	(0.1099)
High Education $\times ln(t)^2$				0.0111		-0.0194	
				(0.1502)		(0.1395)	
Insurance Benefits $\times ln(t)$				0.7661*		$0.7995^{***}$	
				(0.3916)		(0.3859)	
Insurance Benefits $\times ln(t)^2$				-0.1529		-0.1566	
				(0.1002)		(0.1009)	
Duration Insurance Benefits $\times ln(t)$				0.0025		0.0016	
				(0.0025)		(0.0016)	
Duration Insurance Benefits $\times ln(t)^2$				-0.0001		0.0001	
				(0.0005)		(0.0003)	
1992 Reform $\times ln(t)$				-0.5267		-0.6097	
				(0.7717)		(0.8209)	
1992 Reform $\times ln(t)^2$				0.5273*		0.5949***	
				(0.2848)		(0.3023)	
GAV Growth Rate $\times ln(t)$				0.0626		0.0583	
				(0.0640)		(0.0606)	
GAV Growth Rate $\times ln(t)^2$				-0.0029		0.0016	
				(0.0181)		(0.0171)	
Lower-Mid Education $\times ln(t)$				()		()	-0.0999*
							(0.0538)
Lower-Middle Age × Insurance Benefits							-0.0539
							(0.1024)
Upper-Middle Age ×Insurance Benefits							0.1368
· · · · · · · · · · · · · · · · · · ·							(0.1555)
1984 Beform X High Education							-0.1879
ivor norona / ingli Daucation							(0.3296)
1984 Beform X Upper-Mid Education							0.2389
for horona x oppor and Education							(0.2364)
1984 Beform × Lower Mid Education							0.2076***
1984 Reform X Lower-Mid Education							-0.2970
1084 Reform VUpper Middle Age							0.6202***
1304 Reform X Opper-Middle Age							-0.0323 ····
Providuo Employment Carll Dalars 2 V	20						(0.2403)
r revious Employment Spell Below 3 Yea	15						-0.0003
410	10100 50		<b>5</b> 000 10	4011.00	0010.07	2000 <b>F</b> 0	(0.1385)
AIC	16429.53	7515.67	7396.42	6911.99	6913.01	6899.78	15795.03

## Table 5 (cont.): Determinants of the Unemployment Duration.

<u>Note</u>: Robust standard errors in brackets. \*\*\*, \*\* and \* denote 1%, 5% and 10% significance, respectively. Columns (1), (2) and (3) do not include state dependence variables. Column (4) includes a parametric function in ln(t) to allow for state dependence, whereas column (5) uses a non-parametric approach (12 unreported month-dummy variables and cross products with dummies of lower-middle age, days of insurance benefits received and the reforms of 1980, 1984 and 1992). Column (6) controls for Normally-distributed unobserved heterogeneity using the same specification as that of Column (4). Column (7) aims to replicate the specification used by García Perez (1997) for Spain. The variable with the upper index <sup>a</sup> refers in this case to Spain rather than Catalonia, whereas variables with the upper index <sup>b</sup> refer to Catalonia rather than Barcelona.