Employment and Unemployment Transitions in Spain from 1996 to 2005

(Preliminary Version)

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Abstract

In this paper, we have studied the employment and nonemployment transitions in Spain from 1996 to 2005. To do so, we have used a multi-state multi-episode duration model and a censured continuous-time Markovian matrix. By using the censured Markovian matrix, we have been able to balance the negative effect that censure has on the estimated parameters. The results obtained suggest that women have a probability of employment six percent lower than men. In addition, we have been able to show that Spanish employees experience three different stages of employment during their first decade in the labor market.

Key words: *Employment and Nonemployment Transitions, Multi-state Multi-episode Duration Model, Hazard Rate, Censured Continuous-time Markovian Matrix.*
JEL classification: C41, J64.

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1 Introduction

Around one-third of total employees in Spain have a temporary contract and since 1984, the probability of receiving a temporary job offer is much higher than that of receiving a permanent one, see Bover and Gómez (2004). Although this labor market flexibility has sharply reduced the Spanish unemployment rate during the last decade, it has also introduced important income and risk inequalities among different cohorts. Following Bentolila and Dolado (1994), temporary contracts have positively affected insiders (individuals who had permanent jobs), while having a worsening effect on outsiders (individuals who did not have permanent jobs). Thus, outsiders earn lower wages and are also less likely to find a permanent job compared with their insider counterparts. Thus, policy-makers intending to reduce temporary job offers without raising the unemployment rate, should study those personal and economic characteristics that increase both the probability of moving from temporary to permanent jobs and the probability of transitioning from employment to unemployment.

The aim of this paper is twofold. First, we will study those determinants that explain transitions from employment to unemployment and from unemployment to employment in Spain since 1996. To do so, we use longitudinal data from the Spanish Social Security data-base (*Muestra Continua de Vidas Laborales*, MCVL). The advantage of this data-base is that it enables one observe the labor supply history of each individual, and thus to estimate hazards rates with better statistical qualities than those obtained with panel data. Second, we will try to address some common questions such as, which individuals are more likely to be unemployed? Does the previous employment experience increase the likelihood of receiving a job offer?

Similar papers that apply transition data theory have been written before by Bover and Gómez (2004); Olympia Bover and Bentolila (2002); Pérez (1997); and Ahn and Ugidos-Olazabal (1995), among others. They analyze unemployment durations using different hazard specifications, e.g. proportional hazards [Ahn and Ugidos-Olazabal (1995) and Pérez (1997)], logistic hazards [Bover and Gómez (2004)], and logistic hazards with unobserved heterogeneity [Olympia Bover and Bentolila (2002)]. Furthermore, these papers also differ either in the sample analyzed, or by introducing the employment duration into the analysis, Pérez (1997). The main novelties of this paper can be summarized as follows. First, we use a new data base from the Spanish social security that collects information from the first record that Social Security has of each individual through 2005. In contrast, the most recent paper by Bover and Gómez (2004) only has data from 1987 to 1994. Second, most previous papers also include data from significantly higher censured samples compared to MCVL (since MCVL reports the complete labor history of each individual).

In order to obtained most helpful results, we have developed a multi-state multi-episode duration model. Thus, we analyze each individual's labor supply history in calendar time. Furthermore, we have introduce two additional features into our model. First, we have assumed that characteristics do not proportionally affect the hazard rate, as is assumed in the Cox model. Second, we have plugged the estimated hazards into a censored continuous-time Markovian matrix in order to derive the probability of employment over time of those employees who have just entered the labor market. Previous models have used either a semi-Markov matrix because they consider time since the entrance in the spell rather than calendar time, or a continuous-time Markovian matrix without censure.

The remainder of the paper is structured as follows. Section 2 is divided into four subsections. The first subsection briefly presents the two-state model of employment and nonemployment. The second subsection justifies the hazard rate selected. The first optimal conditions for our maximum likelihood estimation are derived in the third subsection. In the last subsection, we describe how to aggregate employment and unemployment probabilities using a censored continuous-time Markovian matrix. Section 3 describes how the sample is selected from the MCVL. Section 4 presents the empirical results. Finally, Section 5 concludes the paper.

2 Statistical Model

2.1 *Two-State Model of Employment and Nonemployment*

During the working lifetime it is likely that an individual will move from the state of employment to the state of unemployment and from unemployment to employment several times. If we want to analyze these transitions, we will need to handle two different stochastic processes: the transition process and the duration process. The transition process is the probability that an individual will move from one state to another, while the duration process is the time that an individual spends in each state. An example of these two processes can be seen in Figure 1, which shows an individual's labor market history. Thus, given that it is likely that an individual will spend time in different states multiple times, we have decided to use a multi-state multi-episode duration model.

According to the previously cited duration model, it is convenient to use the following notation. Each episode, or spell, is distinguished using the subscript k, which belongs to the subset $E = \{1, \ldots, K\}$ of positive integers, where K is the maximum number of observed spells. The state variable is characterized by a series of random variables $\{y_k : k \in E \cup \{0\}\}$, $y_k \in \{1, \ldots, m\}$. However, we have restricted our analysis to the case of two states ($m = 2$). The state of "employment" is denoted 1 and the state of "unemployment or out of labor force" is denoted 2, and thus $y_k \in \{1, 2\}$. Therefore, although in general $\{y_k\}_{k=0}^{K}$ is a random variable, in our case, each spell is associated with a specific state. On the other hand, the time spent by any individual in the spell k, denoted T_k, is a random variable whose distribution is given either by a survival function $S^k(t) = 1 - P(T_k < t)$ or by its failure function $F^k(t) = P(T_k < t)$. Nonetheless, for each individual it is expected that his duration in a state will depend on both personal and economic characteristics. These characteristics, hereinafter covariates, will change according to the individual and the spell that this individual is in. However, we will only take into account time-fixed covariates in order to simplify the model and to reduce the calculation procedure. Hence, we will use a vector of covariates $\mathbf{Z}_k^i$ for the i-th individual in his k-th spell.

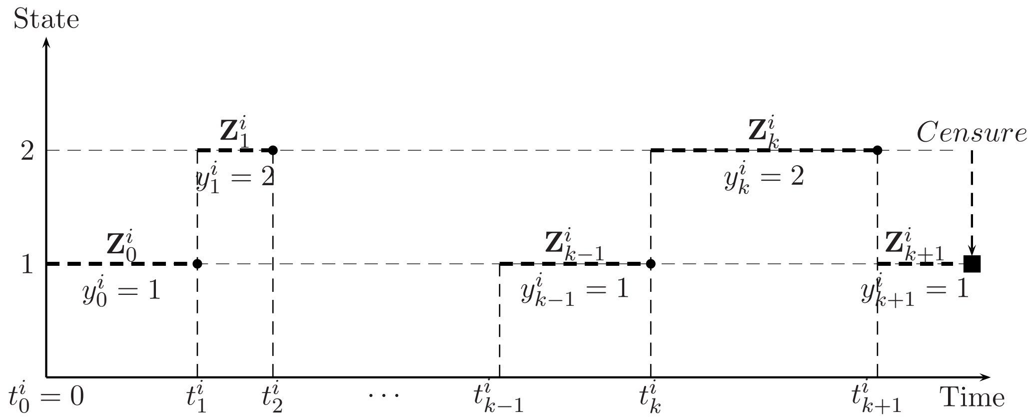
Both the duration and the transition process can be simultaneously characterized by a transition specific hazard rate. In particular, if we assume that the i-th individual is in the state $l \in \{1, 2\}$ at time t, then his probability of exit from the state l to the state j ($j \neq l$), or hazard rate, will be:

$$\lambda_{lj}^k(t|\mathbf{x}_k^i) = \begin{cases} lim_{\Delta t \to 0} \frac{P(t \leq T_k^i < t + \Delta t, y_k^i = j | T_k^i \geq t, \mathbf{Z}_k^i, y_{k-1}^i = l)}{\Delta t} & if \quad t \geq t_{k-1}^i \\ 0 & if \quad t < t_{k-1}^i \end{cases}, \tag{1}$$

where t_{k-1}^i is the ending calendar time of the previous spell to the k-th spell for the i-th individual, as Figure 1 shows. Based on the piecewise equation (1), the associated survivor function in the state $l \in \{1, 2\}$ is:

$$S_l^k(t|\mathbf{Z}_k^i) = \begin{cases} \exp\left\{ -\int_{t_{k-1}^i}^{t} \lambda_{lj}^k(u|\mathbf{Z}_k^i) du \right\} & if \quad t \geq t_{k-1}^i \\ 1 & if \quad t < t_{k-1}^i \end{cases}. \tag{2}$$

Figure 1: Event History in Calendar Time



This figure shows a non-real individual's labor history. The individual starts in the state of employment but, as time goes by, he starts a transition process from employment to unemployment, and vice versa. The time that the individual spends in a state is determined by the points in the x-axis. More concretely, we can calculate the time that this individual spends in his kth spell by subtracting t_{k+1}^i to t_k^i. Finally, whenever our individual arrives at the end of our sample he is right-censured, which means that we no longer observe him from that point on.

We can specify the density function for the kth transition from l to j. This density function is necessary for the maximum likelihood function:

$$f_{lj}^k(t|\mathbf{Z}_k^i) = \lambda_{lj}^k(t|\mathbf{Z}_k^i) \cdot S_l^k(t|\mathbf{Z}_k^i). \tag{3}$$

2.2 *Specification of the Hazard Rate*

In order to contrast the *duration dependence* in the employment-nonemployment duration model, we have assumed that the hazard rate follows a log-logistic distribution. The reasons are twofold. First, the distribution of both unemployment and employment hazard rates usually are described by an inverted U-shaped function. Non-parametric estimations of the data using the Kaplan-Meier method confirm that the hazard rate first increases and then decreases. Second, we need a parametric distribution that will shift the hazard function to the right for each new spell, since we may expect that a further spell will not be attained by an individual at the beginning of the total observation time. Therefore, we will use the following parametric family of the log-logistic distribution:

$$\lambda(t|\mathbf{Z};\theta,\beta)=\frac{\theta t^{\theta-1}(\mathrm{e}^{-\beta\mathbf{Z}})^{\theta}}{1+(t\mathrm{e}^{-\beta\mathbf{Z}})^{\theta}}. \tag{4}$$

The time parameter t is time since the first entrance into the labor market or, equivalently, the total observation time. Note that we have assumed that our hazard rate is non-proportional. As a consequence, covariates will not be independent of time, and thus the vector of regressors β will measure the strength of the effect of the characteristics on the hazard rate over time. This feature thus improves the quality of the results. However, we will have an estimation bias, since we are not controlling for unobserved heterogeneity.

On the other hand, the hazard rate (4) implies that we are able to specify our model as a continuous-time discrete-state Markov chain with alternating renewal processes. This Markovian process will be used subsequently to aggregate individual data as well as to draw the employment-nonemployment probability from the first entrance into the labor market up to time t.

2.3 *Maximum Likelihood Estimation*

Let consider a two-states multi-episode duration model in which it is assumed that all covariates change from spell to spell and that their marginal distribution does not depend on the relevant parameters. Let also consider that every spell is independently distributed. For this model, we can drop the state variable in the hazard rate, since the k-th spell corresponds with a unique state l. The partial log-likelihood function can therefore be written as the sum of the contributions of the N individuals in each spell or episode:[1]

$$\begin{aligned}\ln L(\Theta) &= \sum_{k=1}^{K-1}\ln L_k(\Theta_k)\\ &= \sum_{k=1}^{K-1}\sum_{i=1}^{N}\sum_{l=1}^{2}\delta_l^{ik}\left\{\gamma_k^i\ln\lambda^k(t_k^i|\mathbf{Z}_k^i;\theta_k,\beta_k)-\int_{t_{k-1}^i}^{t_k^i}\lambda^k(u|\mathbf{Z}_k^i;\theta_k,\beta_k)du\right\}\end{aligned} \tag{5}$$

where $\Theta=(\Theta_1,\ldots,\Theta_{K-1})$, being $\Theta_k=(\theta_k,\beta_k)'$, are the parameter vectors to be estimated. θ_k belongs to $\mathbb{R}_+$ and β_k belongs to $\mathbb{R}^q$. γ_k^i is the censured estimator, which takes a value of 1 if the end of the k-th spell of the i-th individual is observed,

[1] We have excluded the kth spell since all remaining individuals are censured.

and of 0 if it is not; t_k^i is the time when we observe that the i-th individual starts his k-th spell; and δ_l^{ik} is an indicator variable that takes values:

$$\delta_l^{ik} = \begin{cases} 1 & \text{if the } i\text{th individual experiences at least } k \text{ episodes and } y_{k-1}^i = l \\ 0 & \text{otherwise.} \end{cases}$$

From (5), the first-order conditions (F.O.C.) for Θ are

$$\frac{\partial \ln L(\Theta)}{\partial \Theta_k} = \sum_{i=1}^{N} \sum_{l=1}^{2} \delta_l^{ik} \left\{ \gamma_k^i \frac{\frac{\partial \lambda^k(t_k^i|\mathbf{Z}_k^i;\theta_k,\beta_k)}{\partial \Theta_k}}{\lambda^k(t_k^i|\mathbf{Z}_k^i;\theta_k,\beta_k)} - \int_{t_{k-1}^i}^{t_k^i} \frac{\partial \lambda^k(u|\mathbf{Z}_k^i;\theta_k,\beta_k)}{\partial \Theta_k} du \right\} = \mathbf{0}_{q+1\times 1}, \tag{6}$$

for $k = 1, \ldots, K-1$. Therefore, the MLE will be distributed asymptotically as

$$\hat{\Theta}_k \sim \mathcal{N}\left[\Theta_k, \left(-E\left[\frac{\partial^2 \ln L(\Theta)}{\partial \Theta_k \partial \Theta_k'}\right]\right)^{-1}\right] \tag{7}$$

2.4 *Aggregation Method: The Transition Matrix*

So far we have obtained both the strength of the effect of the characteristics on the hazard rate and how each hazard rate is distributed over time for each spell. In this section, we use a continuous-time Markov chain to derive the probability for any individual to stay either in the state of employment or in the state of unemployment during his first ten years on the labor market. To do so, we first define our Markov chain:

Definition 1 *Let E be the set $\{1,\ldots,K\}$ of possible episodes, and let $\{\lambda^k, k \in E\}$ be a sequence of transition specific hazard rates. Let also assume that any individual $i \in \{1,\ldots,N\}$ follows an event history labor market that can be characterized by a continuous-time Markov chain $\{\mathbf{X}^i(s), 0 \le s \le t\}$ having state space E and Λ^i-matrix given by*

$$\Lambda_{hk}^i(t) = \lim_{dt\to 0} P(\mathbf{X}^i(t+dt) = h|\mathbf{X}^i(t) = k, \mathbf{Z}_k^i) = \begin{cases} \lambda^k(t|\mathbf{Z}_k^i,\Theta_k) & \textit{if } h = k+1, \\ -\lambda^k(t|\mathbf{Z}_k^i,\Theta_k) & \textit{if } h = k, \\ 0 & \textit{otherwise.} \end{cases} \tag{8}$$

Matrix (8) is a bidiagonal matrix. The principal diagonal is the marginal probability of exiting the kth spell. The secondary diagonal is the marginal probability of reaching the hth spell. In addition, according to (8), an individual can only move between spells in an infinitesimal period of time. This implies that the last spell is not attainable unless the individual has first passed throughout all previous spells.

Once we know the transition matrix $\Lambda^i(t)$ for whichever $t > 0$, we can calculate the probability that the ith individual will stay in any spell at time t.

Definition 2 *Let* $\mathbf{P}(t) = [\mathbf{P}^1(t)\ \mathbf{P}^2(t)\ \cdots\ \mathbf{P}^N(t)]$ *be a* $K \times N$ *matrix.* $\mathbf{P}^i(t) = [\mathbf{P}_1^i(t)\ \mathbf{P}_2^i(t)\ \cdots\ \mathbf{P}_K^i(t)]'$*, for any* $i \in \{1, 2, \ldots, N\}$*, is a column vector of state probabilities, where the sum of* $\mathbf{P}_k^i(t)$ *must be equal to 1.* $\mathbf{P}_k^i(t)$*, for all* $k \in E$*, represents the distribution of probabilities for the different spells or episodes at time t for the* i*th individual. Let* $\Gamma^i = diag(\gamma_1^i, \ldots, \gamma_K^i)$ *be a* $K \times K$ *diagonal matrix of censures. If we define the probability of spending time in any of the possible* K *spells as:*

$$\bar{\mathbf{P}}(t) = \frac{1}{N}\sum_{i=1}^{N}\mathbf{P}^i(t) \tag{9}$$

and the law of motion of $\mathbf{P}^i(t)$ *that predicts the future evolution of the distribution probabilities is*

$$\frac{\partial \mathbf{P}^i(t)}{\partial t} = \Lambda^i(t)\Gamma^i\mathbf{P}^i(t). \tag{10}$$

Thus, we are able to calculate $\bar{\mathbf{P}}(t)$ *for any* $t > 0$*, once the initial state probabilities* $\mathbf{P}^i(0)$ *for all i has been given. In our case, every individual starts in the first spell, thus* $\mathbf{P}^i(0) = [1\ 0\ \ldots\ 0]'$*. Then,* $\bar{\mathbf{P}}(t)$ *becomes*

$$\bar{\mathbf{P}}(t)_{K\times 1} = \left[\frac{1}{N}\sum_{i=1}^{N}\exp\left\{\int_0^t \Lambda^i(s)\Gamma^i ds\right\}\right]_{K\times K} \cdot \bar{\mathbf{P}}(0)_{K\times 1} \tag{11}$$

The aggregate transition matrix, presented in (11), is made up of many different individuals. Therefore, as we are dealing with a nonhomogeneous population, we cannot use the results to represent any specific group of employees. Nevertheless, based on Silverman (1971) we can assume that $\bar{\mathbf{P}}(t)$ is close to the true steady-state solution. Moreover, another feature of (11) comes from the introduction of the matrix Γ. This matrix will balance the negative effect that censure has on the estimated parameters. This is because when we solve the maximum likelihood problem, the estimated parameters are outweighed, and thus the hazard rates estimate a smaller durations. However, these smaller durations are balanced by the matrix of censures, since the latter causes the individual to remain in the censured spell thereinafter.

3 Sample

The data used come from the new longitudinal data-base of the Spanish social security (*Muestra Continua de Vidas Laborales*, MCVL).[2] The MCVL contains labor supply histories of more than 1 million people (4 percent of the total population) who have at least one record in the Spanish social security system before December, 31^{st} of 2005. The advantages of this data-base are: i) it enables one to observe an individual from the time of his/her first record in the social security up until either his/her death or the date that the sample finishes, ii) the sample is large enough to replicate Spanish labor market characteristics. Therefore, given that our aim is to study labor transitions, which occur several times during the working life, this sample fits well with our econometric model.

The MCVL has also important restrictions that are worth mentioning. On the one side, many relevant characteristics such as education, the individual's address, marital status, number of children, head of the household, gross salary, among others are either not available or they are only available for 2005. On the other side, we cannot distinguish between the two states of nonemployment (i.e. "unemployment" and "out of the labor force"). As a consequence, we should take into account that we are introducing biases to the hazard rates from the state of nonemployment to the state of employment, and vice versa (see Flinn and Heckman (1983)).

Given the advantages and the disadvantages of using the MCVL, we have selected a sample of labor supply histories that fulfilled the following criteria. First, we have eliminated those individuals with duplicated records and with records that included missing data. Second, we have only selected employees who were affiliated with the "Regimen General" of the Social Security and did not change their affiliation during the period of analysis. This is because outside of this system we have found the labor supply histories to have too many transitions, which could bias our results. Third, in order to have long labor supply histories without significant changes in the labor market, we have chosen individuals who started working from 1996 onwards. As a consequence, we have only focused on the last ten years of the Spanish labor market. Fourth, we only used individuals older than 16 years old and younger than 45 years old. We have selected this age group to avoid competing

[2]For a detailed explanation of the data base go to the web page:
$http://www.seg-social.es$

risk that arises with individuals who are close to the retirement age. Fifth, we have excluded individuals with more than fifty contracts. An individual with an excessive number of employment transitions is, in general, affected by seasonal adjustments or has transition processes between employment and unemployment which cannot be explained by a stochastic model. Sixth, and most important, we have restricted our sample to individuals with seven or less spells. The reason is twofold. One, because the econometric method is time intensive in terms of computational cost. And two, because in order to analyze transitions from employment to nonemployment and from nonemployment to employment, we need to define a concept of state that transforms the initial sample selected. In particular, we define the employment duration as "the duration of consecutive labor contracts with possible unemployment durations of less than 30 days". In contrast, nonemployment duration is defined as "time spent in the state of unemployment or out of the labor force longer than 30 days".

These previous definitions, although perfectly matched with the econometric model and Figure 1, constrain which characteristics use. For example, in a spell of employment an individual can move from one economic sector to another, change his/her contract from a fixed-term to a permanent contract, move from one firm to another in the same sector, and so on. For this reason, as a first step in our analysis we have only selected three characteristics: age at the beginning of the spell, number of contracts, and quinquennium.

In sum, after filtering the data, we obtain a sample of 123.377 individuals who can experience a maximum of three transitions from employment to nonemployment and another three transitions from nonemployment to employment. This sample is divided into 64.578 men and 58.799 women. The number of spells of employment are 133.906 for men and 123.344 for women, while the number of unemployment spells are 82.648 for men and 80.089 for women. For additional information, sample frequencies of individual variables are provided in Table 1 below.

Table 1: *Sample characteristics by spell and gender*

Episodes	**First**	**Second**	**Third**	**Fourth**	**Fifth**	**Sixth**	**Seventh**
Men							
Number	64.578	46.299	41.050	25.843	21.179	10.506	7.099
Percentage of censure	28,3	11,3	37,0	18,0	50,4	32,4	100
Age:							
From 16 to 20	33.758	23.516	18.189	10.386	7.125	2.988	1.615
From 21 to 25	17.240	12.786	13.288	9.079	8.394	4.485	3.286
From 26 to 35	10.757	7.819	7.747	5.151	4.664	2.504	1.856
From 36 to 45	2.823	2.120	1.759	1.150	920	478	305
Number of contracts							
Mean	2,08	1,93	4,08	3,92	6,18	6,01	8,49
Std. Deviation	2,14	1,98	3,10	2,93	3,83	3,74	4,54
Quinquennium:							
From 1996 to 2000	27.989	15.230	11.097	4.808	3.447	962	684
From 2001 to 2005	36.589	31.069	29.953	21.035	17.732	9.544	6.415
Women							
Number	58.799	44.301	38.246	25.291	19.749	10.497	6.550
Porcentage of censure	24,7	13,7	33,9	21,9	46,8	37,6	100
Age:							
From 16 to 20	24.506	17.229	11.760	7.098	4.343	1.936	889
From 21 to 25	21.574	16.165	16.005	10.463	8.898	4.691	3.115
From 26 to 35	9.906	8.671	8.590	6.376	5.506	3.289	2.228
From 36 to 45	2.813	2.188	1.810	1.263	924	522	280
Number of contracts							
Mean	2,02	1,99	4,04	4,01	6,13	6,13	8,58
Std. Deviation	2,18	2,06	3,16	3,02	3,98	3,87	4,92
Quinquennium:							
From 1996 to 2000	25.214	14.103	9.609	4.243	3.009	842	602
From 2001 to 2005	33.585	30.198	28.637	21.048	16.740	9.655	5.948

4 Empirical Results

In this section we describe the results obtained through the maximum likelihood estimation. We will focus on those characteristics that are able to explain the main differences between men and women. Thus, after analyzing the meaning of the covariates we will present some figures that clarify this issue.

Tables 2 and 3 show the estimated parameters for the log-logistic hazard rate and the results of the covariates by spell. Table 2 presents the results for women and Table 3 does so for men. The observed characteristics included are the age at the beginning of the spell, labeled **EdCom**, age squared or **EdCom2** (to allow nonmonotonic age dependence), the number of contracts up to the end of the spell, which is named **nSOC**, and the quinquennium, **qui**, which is 0 if the spell begins between 1996 and 2000, and 1 if the spell begins between 2001 and 2005. The variable number of contracts has been included in order to analyze the effect that employment transitions have both in the state of employment and of nonemployment. On the other hand, the variable quinquennium has been introduced in order to analyze whether the probability of being employed and unemployed have decreased along the last five years.

Table 2: *Parameter estimates and t-ratios for the event labor history of women (1996-2005)*

Spell	**First**	**Second**	**Third**	**Fourth**	**Fifth**
θ	0.853	2.019	1.262	3.167	1.414
	(250.51)	(400.11)	(174.34)	(466.79)	(119.42)
Constant β_0	0.291	7.940	0.593	7.459	1.707
	(2.12)	(46.77)	(1.42)	(17.50)	(1.85)
EdCom	0.285	-0.154	0.324	-0.113	0.334
	(27.27)	(-12.06)	(10.69)	(-3.61)	(4.82)
EdCom2	-0.004	0.003	-0.005	0.002	-0.006
	(-21.51)	(10.81)	(-9.38)	(3.30)	(-4.34)
nSOC	0.593	-0.003	0.198	-0.025	0.104
	(90.90)	(-0.32)	(47.72)	(-1.65)	(16.80)
qui	-0.215	-0.170	-1.353	0.162	-2.019
	(-12.14)	(-8.25)	(-27.59)	(2.74)	(-15.21)

Note: A positive sign means that the covariate decreases the hazard rate, while a negative sign means that the hazard rate increases.

The analysis of the set of parameters $\{\theta_k, \beta_{0k}\}_{k=1}^{K}$ helps one understand how the parametric hazard rates are distributed. On the one side, if θ_k is less than one, the duration dependence in the kth spell will be negative, which means that the exit rate from the kth spell decreases as time goes on. In contrast, if θ_k is greater than one, the duration dependence in the kth spell will be positive at the beginning, and negative afterwards. On the other side, the constant variable β_0 represents the maximum marginal probability level that the hazard rate reaches. More specifically, the higher the value of β_0, the lower the hazard rate becomes.

Therefore, Tables 2 and 3 show that the distribution of the first spell does not have the same distribution as subsequent spells of employment.[3] Thus, Figure 2 shows the longer the time spent in the first employment spell, the lower the marginal probability of exiting to the state of unemployment becomes. Furthermore, an important characteristic that appears in every spell of employment is that women always present a lower probability to stay employed, as β_0 is always higher for men than for women. By analyzing the subsequent states of employment, we see how employees have a greater chance of transitioning to unemployment during the first months, because their duration dependence is positive.[4]

Table 3: *Parameter estimates and t-ratios for the event labor history of men (1996-2005)*

Spell	**First**	**Second**	**Third**	**Fourth**	**Fifth**
θ	0.870	2.277	1.200	3.656	1.277
	(255.68)	(506.15)	(157.47)	(581.33)	(101.36)
Constant β_0	1.602	6.570	1.786	5.725	5.289
	(13.56)	(38.98)	(5.42)	(10.98)	(7.74)
EdCom	0.205	-0.042	0.228	0.050	0.045
	(22.02)	(-3.09)	(9.43)	(1.17)	(0.87)
EdCom2	-0.003	0.0002	-0.003	-0.002	0.000
	(-15.67)	(0.81)	(-7.10)	(-1.72)	(0.02)
nSOC	0.611	-0.015	0.221	-0.039	0.134
	(100.41)	(-1.49)	(53.24)	(-2.37)	(19.39)
qui	-0.190	-0.146	-1.286	0.091	-2.411
	(-11.39)	(-7.19)	(-27.87)	(1.78)	(-15.16)

Note: A positive sign means that the covariate decreases the hazard rate, while a negative sign means that the hazard rate increases.

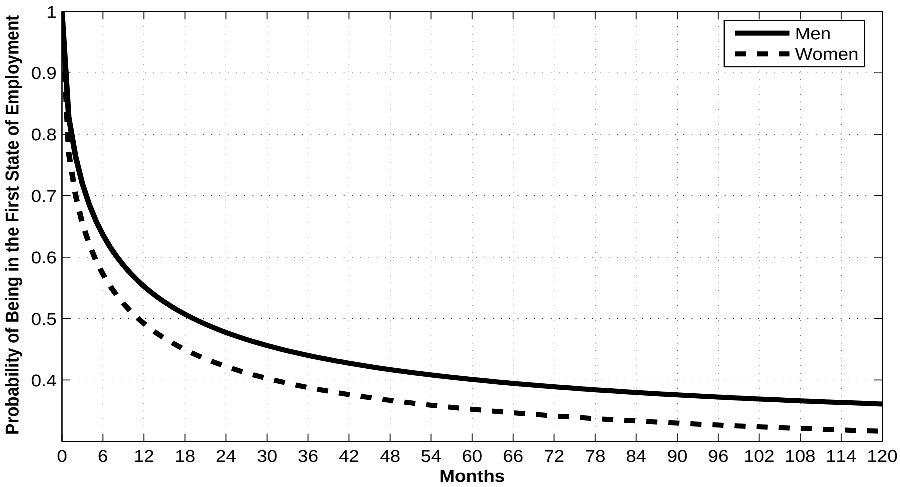
The hazard rates for both men and women in the state of unemployment present a positive duration dependence during the first six months while after this period of time the duration dependence is negative (θ values are always greater than one). This result is similar to that presented by Pérez (1997) for Spanish employment transitions from 1987 to 1993.[5] In sum, we can state that employment and unemployment durations have a different distribution over time, as it was expected.

[3]This result is consistent with Flinn and Heckman (1983).

[4]Although we are not controlling for contract type, we may expect that this is due to temporary jobs of six months.

[5]Nonetheless, we could obtain better results if we were to control for unemployment benefits.

Figure 2: Employment Probability in the First Spell, By Gender



The effect of age on the hazard rate varies according to the gender and the spell. In general, age has a positive effect for both sexes while the individual is employed; however, the effect is negative when the individual is unemployed. In addition to the latter fact and by using EdCom and EdCom2 reported in Tables 2 and 3, we are able to determine the age-cohort with the lowest exit rate when the individual is employed, and the greatest exit rate when the individual is unemployed:

Table 4: *Minimum and Maximum Exit Rates by Age-Cohort and Spell (1996-2005).*

	Minimum Exit Rate TO UNEMPLOYMENT			Maximum Exit Rate TO EMPLOYMENT	
Spell	**First**	**Third**	**Fifth**	**Second**	**Fourth**
Men	29	38	(-)	(-)	(-)
Women	35	33	27	28	26

Note: (-) t-student test does not reveal significant statistical difference from zero.

Table 4 reports that the age of a woman is a key variable in explaining employment and unemployment durations. Nevertheless, the age of a man is only significant during his first and second period of employment.[6] Furthermore, if we analyze the age-cohort with the lowest probability of being unemployed, Table 4 shows that important differences between men and women exist. For example, for the group of men who have never been unemployed, those who start working with 29 years of age have the greatest probability to continue being employed and, moreover, those men who are 38 years old and have experienced one period of unemployment have the lowest exit rate to unemployment. On the contrary, Table 4 reports that, in the case of women, the age of entrance into the labor market with the lowest probability of being unemployed depends negatively on the number of previous unemployment situations. Unfortunately, we cannot control by education and number of children in order to explain this fact.

The variable nSOC, or number of employment transitions up to the end of the spell, positively affects the duration the individual is employed. But this effect decreases with the number of unemployment situations. In contrast, the greater nSOC is, the lower the probability of being hired becomes. Nonetheless, when the individual is unemployed for the first time, this variable is not significantly different from zero.

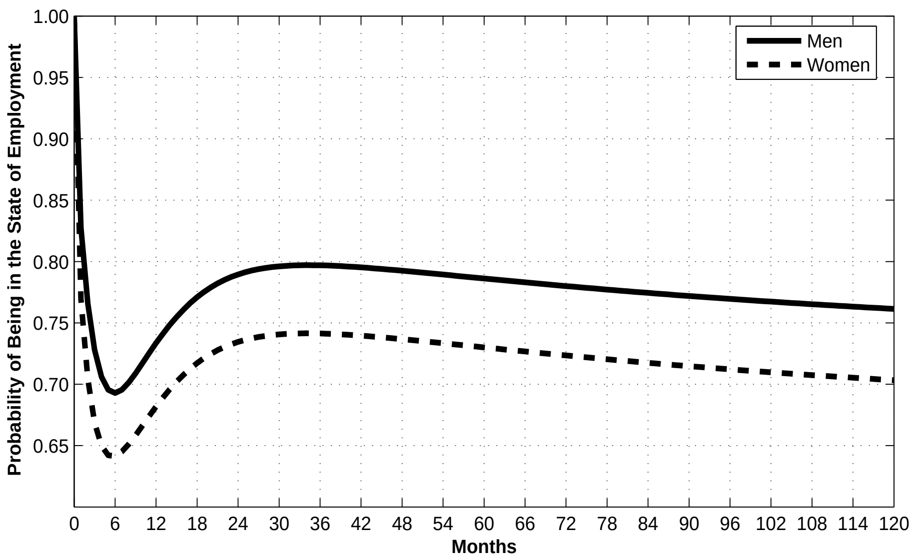
According to the estimations of the variable *qui*, which are at the bottom of Tables 2 and 3, the duration of employment was shorter during the period 2001-2005 than during the period 1996-2000. Nevertheless, this negative effect was balanced with shorter first-time unemployment durations during the latter period.

Finally, given the estimated results and using equation (11), we are able to plot the probability of employment over time. Figure 3 shows that we can divide the first ten years in the labor market into three periods: from 0 to 6 months, from 6 months to 3 years, and from 3 to 10 years. During the first period, employees begin with fixed-term contracts of three, six, and twelve months in order to obtain experience. Thus their probability of transitioning to unemployment increases sharply. We have estimated that only 36 percent and 31 percent of men and women, respectively, do not leave their first spell of employment after ten years. After the first six months, from the first entrance into the labor market up to 3 years, we see that employees consolidate their employment situation. In fact, many individuals who began an unemployment episode do find a new job. Unfortunately, 10 percent of men and

[6]We have only studied individuals that began working before they were 45 years old.

12.5 percent of women experience a period of long term unemployment or leave the labor force during their first unemployment (see Figure 4). Third, from three years onwards, an employee has a low, although increasing over time, probability of failing. Besides these three periods, it is easily seen from Figure 3 that there exists an important difference in the probability of employment between men and women. Specifically, this probability is always six percent higher for men than for women.[7] This circumstance is due to the higher negative duration dependence that women have at the end of both employment and unemployment spells. Figure 4 shows how the probability of leaving unemployment declines with the duration of unemployment, as in Andrés et al. (1989). However, the latter circumstance does not

Figure 3: Probability of Being Employed Over Time By Gender



cause any difference in the number of labor transitions between men and women, see Table 5 below. Note that the stationary probabilities are rather similar for both sexes. Therefore, during the first decade in the labor market women have similar labor histories to men in terms of transitions, but not in terms of durations (i.e. shorter employment durations and longer unemployment durations than men). Thus, we have estimated that the mean number of months worked during the first 10

[7]Therefore, we can use a Cox model in order to study differences by gender.

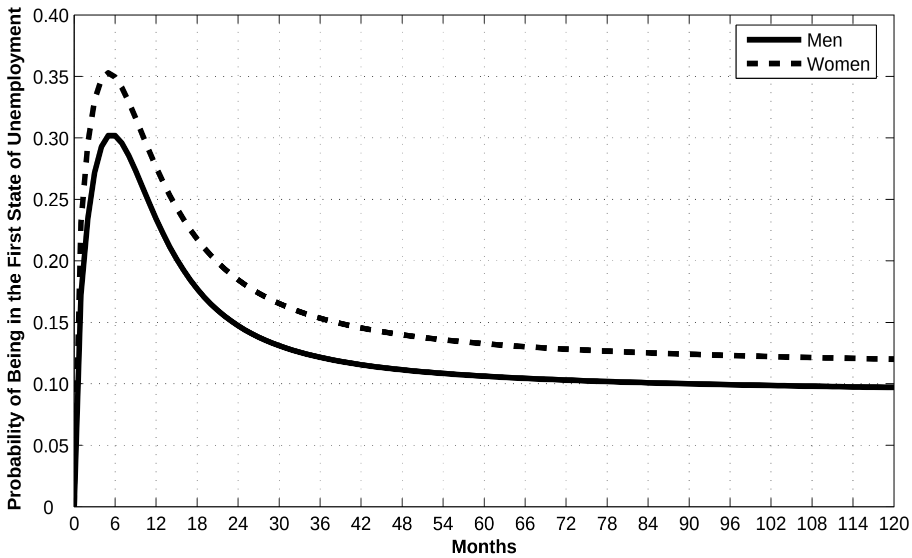
years (120 months) are 95 months and 88 months for men and women, respectively.

Table 5: *Stationary Distribution in the State of Employment according to the Number of Unemployment Situations (1996-2005), By Gender.*

Number of Unemployment Situations	**Women**	**Men**
0	42,48	45,09
1	33,40	32,64
2	18,59	17,46
3	5,53	4,80

During the first decade in the labor market, the majority of individuals (76 percent) only experiences at most one unemployment situation.

Figure 4: First-Time Unemployment Probability Over Time, By Gender



The probability of being unemployed during the first six months increases sharply. Subsequently, the majority of people who are unemployed after six months in the labor market find a new job during the next two years, with a greater probability during the first six months of job hunting. Finally, we can consider those people who remain unemployed after 36 months, to be either in a state of long term unemployment or out of the labor force.

5 Conclusions

In this paper, we have studied the employment and unemployment transitions in Spain from 1996 to 2005. For this purpose, we have used a multi-state multi-episode duration model and a censured continuous-time Markovian matrix. By using the censured markovian matrix we have been able to balance the negative effect that censure has on the estimated parameters.

Our main empirical results suggest the following. One, in the first decade in the labor market women have similar labor histories to men in terms of transitions, but not in terms of durations. In particular, women present shorter employment durations and longer unemployment durations than men. Thus, the employment probability for women is, on average, six percent lower than for men during the decade. Two, employees pass through three stages during the first decade of employment. The first one takes place during the first six months of employment. This period seems to be unstable and is associated with the greatest probability of unemployment. The second period begins after six months and lasts 3 years. During this stage, employees consolidate their employment situation and their probability of employment increases. Finally, once the individual is consolidated into the labor market, the last period is associated with a slow decrease in his/her probability of employment.

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