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Universidad Carlos III de Madrid
Calle Madrid, 126 (Office 6.0.02)
28903 Getafe (Madrid), SPAIN

UNEMPLOYMENT BENEFITS AND RECALL JOBS IN SPAIN: A SPLIT POPULATION MODEL

José M. Arranz, *Universidad de Alcalá*

Fernando Muñoz-Bullón, *Universidad Carlos III de Madrid*

Abstract: We study unemployment insurance benefit recipients' transitions out of unemployment, focusing on whether they are recalled to the previous employer. For this purpose, we develop a split population model of the recall decision by employers, since only a portion of unemployed workers is ever recalled. Age, qualification, contract type, previous tenure and wage levels, and the level of benefits are important determinants of both whether and when a recall to the previous employer is initiated.

Key words: unemployment insurance, recall jobs.

Introduction

Several studies have stressed that individual transitions out of unemployment depend on the extent to which recall by the previous employer is expected (Rosholm and Svarer, 2001; Jensen and Svarer, 2003; Røed and Nordberg, 2003). Despite this prior research and the fact that in Spain around a third of jobless workers return to the firm where they were previously employed (Alba et. al., 2007), research on unemployment duration in this country has traditionally given little attention to the outcome of return to the previous employer. Instead, prior research has mainly focused on the generosity of the unemployment compensation system and its impact on the exit out of unemployment (see, e.g., Alba-Ramírez, 1999; Bover *et al*., 2002; Gonzalo, 2002; Jenkins and García-Serrano, 2004; Arranz and Muro, 2007; Arranz *et al*., 2009). Only recently has research in Spain distinguished spells that end in recall (i.e., workers returning to the previous employer) from those that end in exit to a new job (Alba et. al., 2007, 2012). As these authors underlined, a better understanding of the recall behaviour by the unemployed is important for labour market policy and measures addressing joblessness. Specifically, distinguishing recall to the same employer from reemployment into a new job becomes useful to understand the influence of individual and job characteristics on the unemployment hazard rate. These authors found the length of time workers collect unemployment benefits to be significantly affected by firms' recall decisions.

Previous research distinguishing the two mentioned exits from unemployment (recall versus new job) was based on standard duration models. A standard duration model produces estimates of how variables affect the hazard, but requires (and assumes) the probability of recall for all cases to be one. That is, hazard models generally make distributional assumptions that effectively require all cases to eventually experience the hazard (i.e., be recalled). This would be no inconvenient provided that the event in question (the recall) was universal —i.e., that recalls were experienced by everyone in the population (Cox and Oakes, 1984). However, this distributional assumption will not be met if the cases are heterogeneous, so that some cases have zero (or close to zero) recall probability. As commented above, because the majority of jobless workers are not recalled in Spain, we find it hard to accept the standard duration model's assumption that every individual will eventually be recalled. Therefore, the motivation of this paper is to provide an empirical analysis on the determinants of the length of time until a recall occurs among a sample of unemployment benefit recipients, allowing for the possibility that some individuals will never be recalled. The relevance of our analysis also lies in the fact that duration in the unemployment benefit system in Spain is important for UI policy concerns. Specifically, if before searching more intensively for a new job as benefit exhaustion approach, benefit claimants attempt recall from their previous employer, this may imply that the Spanish UI benefit system (which is nearly fully subsidized, in the terminology of Feldstein) offers an implicit subsidy to firms that rely heavily on temporary layoffs and to workers interested in only part-year work. If this were the case, there would exist a tendency for individuals to fall into a trap of repeat use of the UI system. In this regard, we analyze whether there are a significant influence of firms' recall policies as determinants of duration of workers' unemployment benefit spells.

For this purpose, we estimate two models based on two competing assumptions. The first model takes the standard assumption in duration models that all benefit recipients eventually end in a recall job. The second one is a split population duration model which takes into account the possibility that some benefit recipients will never be recalled to his/her previous employer. This way, we avoid conflating the speed and proportion of recalls, which is typical of standard unemployment duration models. Because split population models are designed to examine research problems where there is a proportion of long-term survivors —i.e., people who never experience the event (Maller and Zhou 1996)— our analysis allows us to measure the effects of our independent variables on *whether* a recall will occur, as well as their influence on *when* such event happens. We thus make an empirical contribution to the extant literature that applies “cure models”, which have a history of extensive implementation in social sciences, where the assumption that all observations will eventually fail is often unrealistic. Cure models offer a more realistic alternative to modelling these data. This literature has had both a long history (e.g. Boag 1949; Berkson and Gage 1952) and widespread applications (e.g. Vaupel et. al. 1979; Farewell 1982; Aalen 1988, 1992; Kuk and Chen 1992; Longini and Halloran 1996; Maller and Zhou 1996; Tsodikov 1998a, 1998b; Price 1999).

The paper is organised as follows. Section 2 gives a brief description of the unemployment insurance benefits in Spain. Section 3 presents the dataset and provides some basic facts on recalls and unemployment benefits. Section 4 discusses the econometric models, distinguishing the traditional duration model from the split population duration model. Section 5 provides the estimation results. Finally, some concluding remarks are presented in section 6.

Unemployment insurance benefits in Spain

In Spain, individuals who have lost their job involuntarily—including the end of fixed-term contracts—and have worked for 12 months or more during the six years preceding unemployment are eligible for UI benefits. Individuals who have worked for 12–17 months can receive UI for up to 4 months. Those who have worked for 18–23 months can receive up to 6 months, and so on up to a maximum of 24 months of UI for those who have worked for 72 months or longer. The amount of UI is determined as a percentage of the average wage in the 12 months preceding unemployment: 70% during the first six months of unemployment and 60% for the remaining period of eligibility. The minimum amount is 75% of the statutory minimum wage (SMW) if the worker has no dependent children (100% if he has dependent children). There is also a maximum equal to 170% of the SMW, which is raised to 190% (220%) if the unemployed person has one (two or more) dependent child (children).

One key institutional difference between the UI systems in Spain and those in other countries is the absence of the no experience rating in the Spanish UI tax system[i]. As a result, the unemployment benefit system contains a subsidy element that can lead to an extensive use of recalls. Since UI claimants expecting to be recalled have less of a tendency to search for a new job,[ii] individuals may repeatedly cycle between UI and employment with the same employer (Alba et al., 2012). For instance, some individuals might work for the minimum amount of time needed to qualify for benefits (1 year), collect benefits for as long as possible (up to 4 months), be recalled to the previous employer and, finally, repeat the cycle. Thus, instead of searching for a new job, UI recipients may wait for a recall from their previous employer as of the time the benefit is exhausted. At the same time, employers may synchronize their recall decisions according to the unemployment benefit entitlement because laying off a worker with a high potential entitlement is less costly to the firm than laying off an equally productive worker with a low potential entitlement—the former will be less likely to find a new acceptable job with an alternative employer than the latter (Pissarides, 1982).

The dataset

This paper uses the Spanish “Continuous Sample of Working Life” data set (*Muestra Continua de Vidas Laborales*, hereinafter MCVL). This administrative dataset contains information on all employment and insured unemployment spells of a 4 percent random sample of Spanish individuals who had some relationship with the Social Security across the period 2004-2010. The MCVL dataset is made up of several files containing diverse information. The personal file includes information on individual characteristics (gender, age, province of residence and nationality). The Social Security files contain details on firm and job attributes (employer size, industry affiliation, qualification level, type of contract, tenure, and reason for termination of the spells). The MCVL dataset contains accurate and detailed information on the jobs held by the individuals who entered insured unemployment. Moreover, the dataset contains an anonymous identification number for the employer associated with every single spell of employment. Thus, recalls are identified by whether or not each firm's identification numbers of two subsequent employment spells coincide. This allows us to know whether job losers were immediately rehired by the same or a different employer[iii].

The MCVL also provides information on the unemployment benefits received by each worker (in the event they are eligible for them), the type of benefits received (UI or UA) and the number of days of benefit receipt[iv]. Nonetheless, in order to collect information on the wages received by the individuals included in our sample in the previous job and on their level of UI benefits, we have merged this dataset with a separated 'tax module' in the MCVL provided by the Tax Administration National Agency (*Agencia Tributaria*, AEAT), which gives annual data on different types of income received[v]. In particular, we have linked the wages and the level of UI benefits contained in the aforementioned tax module with the Personal and Social Security files because, as it is well known, tax earnings data do not suffer either from measurement errors (which are common in self-reported wages) or from top coding (also common in administrative data like Social Security records) —these two problems make tax data far more reliable. Another fact that reassures us in the use of tax data is that results are fully comparable to the ones obtained with other sources such as the Quarterly Labour Cost Survey (from the Spanish National Statistics Institute) —in the case of wages— and the labour statistics published by the Spanish Public Employment Service —in the case of the amount of unemployment benefits (see Arranz and García-Serrano, 2011b)[vi].

In the present study, we use a subsample of the MCVL complete dataset. The selection consists of a representative sample of individuals whose employment spells ended at any time of the year 2005 and who complied with the following criteria: 1) Entered unemployment insurance (UI) due to involuntary reasons —i.e., the end of temporary contracts, layoffs and other involuntary reasons; 2) Were wage and salary workers in the non-agriculture private economy (i.e., the individuals selected were registered in the General System of Social Security in the previous job); 4) Were between 16 and 59 years-old at the time of starting UI (to avoid complications associated with early retirement). 5) We have information of wages and amount benefit data contained in the tax module about recipients. After applying this sample selection, we obtain a final sample of 50,140 (1,253,500 weighted) spells of unemployment insurance after individuals have lost their job in 2005.

[TABLE 1]

Table 1 presents the descriptive statistics of the sample used in the empirical analysis. In this table, censored observations correspond to individuals who exhaust UI benefits. Therefore, out of the total sample, 6,855 observations correspond to censored observations (13.67% of the entire sample). The values of all the variables are measured at the beginning of the UI spell. As Table 1 shows, 33.89% of unemployed who find a job return to the firm where they were previously employed. Therefore, recalls do constitute, indeed, an important element of unemployment in Spain (this figure is coherent with prior literature; see, e.g., Alba et al., 2007, 2012, or Arranz and García-Serrano, 2011a), and is even higher than the one found in other European countries (Mavromaras and Rudolph, 1998; Mavromaras and Orme, 2004). In addition, the recall outcome is concentrated on certain individuals. Women are particularly more likely than men to return to the previous employer (55.6 percent of recalled individuals are women). The recall outcome is also more prevalent among individuals above 30 years-old, manual qualified workers (BCHS, BCMS and BCLS), workers with relatively short tenure in their previous job, those who held either a temporary or a permanent-per-task contract, and those previously hired in firms with more than 250 employees in the business activities and financial intermediation, and in real estate and renting industries.

Methodology

Econometric approach: split population model for the recall outcome

As already stated above, one assumption of standard duration models is that every observation in the data will eventually experience the event of interest (in our case, a recall). Schmidt and White (1989) relaxed this assumption by essentially "splitting" the observations under analysis into two subpopulations: one that would eventually experience the event of interest and one that would never experience the event. In our analysis, we are interested in the factors that explain the timing of recalls after the individuals' job loss in 2005. Because a standard duration model (SDM) cannot account for the fact that not all these unemployed individuals are recalled by their previous employer, in this section we describe the split population duration model (SPDM), which accounts for the possibility that some individuals will never be recalled. Specifically, following Schmidt and Witte (1989), we specify a model that generates two sets of simultaneously estimated coefficients: (1) coefficients for the effects of covariates on the incidence of the recall occurring, and (2) coefficients for the effects of covariates on the *timing* of the recall, conditional on the recall occurring. Therefore, the probability of eventual recall is an additional parameter to be estimated, and may be less than one. More formally, we define a latent variable F that is equal to one for cases that eventually end in recall and zero for cases that are not likely to end in recall; this variable is unobservable. Let:

$$\Pr(F=1)=\delta \tag{1}$$

$$\Pr(F=0)=1-\delta \tag{2}$$

Where δ is the rate at which unemployed individuals are recalled. When $\delta=1$, all individuals would eventually be recalled, and the population will not be characterized by the unobserved split between recall and new job. Now, let Y be the observable variable indicating whether individuals actually experience the recall hazard. For individuals that are eventually recalled, *Y=1* (*Y=0* for individuals not recalled).

Next, assume a distribution function, $G(t|F=1)$ with density $g(t|F=1)$, both conditional on *F=1* because the hazard is irrelevant where the probability of recall is 0. Thus, for individuals who are recalled, we observe *Y=1*, and so *F=1*, and the density is:

$$\Pr(Y=1)=\Pr(F=1)g(t|F=1)=\delta\, g(t|F=1) \qquad (3)$$

Whereas for non-recalled individuals, *Y=0*, and *F* is unknown, so the probability of *Y=0* is:

$$\Pr(Y=0)=1-\delta+\delta\,[1-g(t|F=1)] \qquad (4)$$

Therefore, the SPDM is applied to account for a specific type of heterogeneity, i.e. the possibility that some individuals will never experience a recall while others will. What we are estimating here is, first, the probability of being recalled and, second, the timing of this event conditional on the probability of being recalled. The probability of failure δ can be estimated via a *probit* or *logit* model, and thus can be specified as a function of a set of independent variables[vii]. Thus, the model consists of two equations; the first one estimates Pr(*recall*), and the second estimates the hazard given the probability of recall and a set of independent variables —$h(t|recall,x)$. The hazard in the SPDM is conditional on the probability of ever being recalled. Note that if $\delta=1$, the SPDM reduces to the SDM (which presumes that all individuals are eventually recalled).

The time-to-recall or hazard model can be estimated via any of the parametric or semi-parametric specifications commonly used in the literature. Thus, the general shape of the hazard function will be constrained by the functional form of the probability distribution $G(t)$ imposed on the data. Given the potential negative stigma associated with unemployment (the time in unemployment may serve as a signal that the person has not received any offer), we expect the recall hazard to first rise rapidly, and then decline over time. This intuition is borne out in figure 2 (see next section), which shows the Kaplan Meier recall hazard rate for the whole sample. The largest number of recalls occurs in the first year after the individual became unemployed. For this reason, we use the log-logistic distribution in our tests, a relatively flexible form that yields a hazard function that is non-monotonic in *t*. This flexibility is essential to test whether the recall failure follows a non-monotonic, life cycle type pattern (as suggested in figure 2). The log-logistic duration model assumes that *ln(t)* has a logistic distribution with mean 0 and variance πγ/√3 (Greene, 1997, p. 989). This yields the following functional forms of the survival and hazard functions:

$$S(t) = \frac{1}{1+(\lambda t)^{p}} \tag{5}$$

$$h(t) = \frac{\lambda p(\lambda t)^{p-1}}{1+(\lambda t)^{p}} \tag{6}$$

where the estimable parameters *p* and λ give the hazard function its exact shape. The parameter *p* (known as the scaling parameter) determines the rate at which the hazard rate increases or decreases across time: if $p<1$, the log-logistic hazard increases and then decreases. If $p \geq 1$, then the hazard is monotone decreasing[viii]. The parameter λ determines the portion of the hazard rate that is time-invariant. We estimate these parameters using maximum likelihood techniques and the following likelihood function:

$$L = \prod_{i=1}^{N} [\delta g(t_i \mid p, \lambda)]^{Q_i} [(1-\delta) + \delta S(t_i \mid p, \lambda)]^{1-Q_i} \tag{7}$$

where Q_i = 1 if individual *i* is recalled during the sample period (for uncensored observations); Q_i = 0 if individual *i* survived the sample period or is not recalled during the sample period (for censored observations). The split parameter δ is the estimated mean probability of individuals experiencing the event of interest. Thus, the model collapses to a standard duration model for *δ=1,* in which *S(t)* and *g(t)* are estimated assuming that all individuals are eventually recalled; while for δ <1 both *S(t)* and *g(t)* are estimated conditional on the probability of failure.

Of the three estimable parameters in the likelihood function (δ, λ, and *p*), the probability of recall *δ* and the cross-sectional parameter *λ* can be made individual-specific as follows:

$$\delta_i = \frac{1}{1+e^{\alpha' X_i}} \tag{8}$$

$$\lambda_i = e^{-\beta' X_i} \tag{9}$$

where X_i is a vector of individual-specific and time-invariant covariates, and the parameter vectors α□□and β□are to be estimated[ix]. The estimated α□'s measure the impact of the covariates on the probability that an individual will survive —a negative α□□indicates that the covariate is associated with a lower probability of survival (a higher probability of recall). The estimated β's measure the impact of the covariates on the individuals' unemployment duration until a recall is observed —given that a recall occurs, a negative β□□coefficient indicates that the covariate is associated with a shorter duration (a faster failure). Thus, we have a very flexible specification in which the shape of the hazard function, the probability of survival, and the time-to-failure can all vary from individual to individual.

Finally, we also estimate a "standard" duration model (SDM) whose dependent variable is the length of time between the individual's getting unemployed and its subsequent recall. For this purpose, we specify a log-logistic duration model, which assumes that *ln(t)* has a logistic distribution and yields the following functional forms on the survival and hazard functions:

$$S(t) = \frac{1}{1 + (\lambda t)^{\frac{1}{p}}} \qquad (10)$$

$$h(t) = \frac{\lambda^{\frac{1}{p}} t^{\frac{1}{p}-1}}{p\left[1 + (\lambda t)^{\frac{1}{p}}\right]} \qquad (11)$$

where $\lambda = e^{-\beta' X_i}$, and *p* is the scale parameter, which determines the shape of the distribution, is estimated from the data.

Non-parametric analysis

In this section we perform a non-parametric analysis based on life table estimation. This explanatory analysis will provide a first impression of what kind of profile the data exhibit. Duration is defined as staying in the original state (i.e., perceiving unemployment benefits) until a transition to employment occurs via recall or a new job. If none occurs during the time period of our analysis, the episode is considered as censored. Consequently, our definition of unemployment duration refers to the number of consecutive days being registered as receiving UI benefits. Plots of the Kaplan-Meier estimate of the survival function for the sample which includes both recalled and non-recalled individuals, and for the sub-sample of recalled individuals only are presented in figure 1. The Kaplan-Meier estimates of the survival function using the full sample yields a survival function which reaches a limit at around 0.42. The Kaplan-Meier estimates of the survival function on the sub-sample who has been recalled show a much steeper descent and approaches zero for durations above 600 days, showing that virtually every individual has been recalled by that time.

[FIGURE 1]

The time profile of the empirical hazard (product limit estimates of the hazard function for the recall outcome) is presented in figure 2. The hazard rate of ending in a recall at a given moment of time is defined as the probability of being recalled at that moment, given that the benefit recipient has not been recalled previously. This Kaplan-Meier hazard curve implies that the recall hazard rises steeply, reaches a maximum, and then gradually declines. Thus, it is evident its non-monotonicity; the recall hazard rises to a peak 120 days after the individual gets unemployed, then declines monotonically after that. This non-monotone shape suggests that a log-logistic or log-normal specification provides a suitable fit for the data, as already commented in section 3.1 above.

[FIGURE 2]

In any case, if the incorrect distribution is chosen to model the unemployment hazard rate, the parameter estimates may be biased. In this regard, we have used several diagnostic tests for misspecification in our models. First, we check whether the predicted proportion of the recalled unemployed individuals obtained from the split duration model is close to the actual proportion observed in the data. Thirty six percent of the sample is eventually predicted to be recalled, which is very close to the proportion of recalled individuals observed in the dataset (33%).

Second, we use plots of the cumulative Cox-Snell residuals for the observed failures in the sample to assess the general fit of the SDM and of the SPDM (for a general discussion of Cox-Snell residuals, see Klein and Moeschberger, 1997). This plot of residuals after fitting a parametric model to survival data is one of the most useful tools, and consists of comparing the distribution of the Cox-Snell residuals with the unit exponential distribution. A correctly fitted model should yield cumulative Cox-Snell residuals which resemble a (censored) sample from a standard exponential distribution. A plot of this parametric estimate of the cumulative hazard function for these data should therefore lie on a 45º line through the origin. This comparison is made using a cumulative hazard, or log-cumulative hazard, plot of the residuals. In summary, the Kaplan-Meier estimate of the survivor function of the Cox-Snell residuals —$\hat{S}(r_{Ci})$— is obtained, and $-\log\left(\hat{S}(r_{Ci})\right)$ is plotted against r_{Ci}. A straight line with unit slope and zero intercept should be obtained if the fitted model is appropriate[x]. The cumulative hazard plots of the Cox-Snell residuals are given in figures 3 and 4 —figure 3 (4) plots the cumulative Cox-Snell residuals for the SDM (SPDM). In figure 3, comparing the lines, we observe what would be considered a concerning lack of fit. The deviation from the 45º line indicates some misspecification. On the contrary, figure 4 shows that the line of the cumulative hazard has an intercept and slope close to zero and unity, respectively. Thus, the plot for the Cox-Snell residuals for the SPDM (calculated for the sub-sample of recalled individuals, see Figure 4) provides a substantial good fit (as expected).

[FIGURES 3 AND 4]

Estimation results

Table 2 shows estimation results for both the SPDM described above and, for comparison, for the standard log-logistic duration model (SDM). The first three columns in this table give the parameter estimates for the SDM, and the next six columns present model estimates for the SPDM. As regards the latter model, the first set of coefficients relates to the recall duration and the second set of coefficients relates to the probability of ever being recalled. The SPDM, as already commented, weights the likelihood of each observation by using the estimated probability that the individuals will ever be recalled —although it is unknown a priori which people will eventually be recalled to the same employer, a logit function is estimated to describe the probability that any individual will do so—, whereas the traditional non-split duration model assumes that all of them will eventually do so. Parameters in both types of duration models are presented in terms of the “accelerated failure time” (AFT) parameterization. This parameterization presents coefficients in terms of their relationship to expected failure times. A negative sign on a coefficient under this parameterization implies that the duration is "shortened" by some value per unit change in the covariate (i.e., the expected time-to-recall is sooner rather than later). Therefore, a negative coefficient implies an *increase* in the hazard rate, while a positively signed coefficient implies a *decrease* in the hazard[xi].

[TABLE 2]

As regards estimation results from the SPDM, males are less likely to be recalled —being a male reduces the probability of a recall by 34 per cent—, and in case of being recalled, they are recalled later than women. In addition, although age is only an important determinant of whether a recall occurs for individuals above 44 years-old (these individuals are the most likely recalled), in case that a recall occurs, age reduces the recall duration: individuals 24 years-old and older are recalled earlier than individuals under 24 years-old. This finding that younger workers are recalled later than elder workers is likely related to the fact that older workers enjoy more firm-specific human capital, which is an attribute highly valued by the employer. Workers' possession of human capital and its high cost of acquisition may therefore explain why firms are not interested in risking acquired human capital of eldest workers. In addition, it is a fact that younger workers are more willing to move from jobs (and employers) for improving their job match and eventually settling in a more stable career path (Jensen and Svarer, 2003).

Although the data set does not contain variables related to the individual's educational attainment or occupation, it does provide information related to the required level of qualification for the job (job category). The dummies collecting this information prove to be important determinants of both whether and when a recall to the previous employer is initiated. In particular, we find that highly White Collar High Skilled workers (WCHS) are recalled sooner by their previous employer than their remainder ones. This result, combined with that related to age and sex is qualitatively similar to those found in Alba et. al. (2007), and fit quite nicely into a variety of theories suggesting that the accumulation of firm-specific human capital by older workers, the job-shopping behaviour of younger workers, and the level of qualifications are good explanatory factors of the probability of exiting from unemployment via a recall (Fischer and Pichelmann, 1991).

As seasonal downturns in demand and production are easily anticipated by employers, they may turn to lay-off workers temporarily as an employment adjustment strategy. This expected relationship between seasonal work and recalls is captured through the variable *contract in previous job*. Holding a fixed-term contract in the previous job (temporary, casual contract, or other fixed-term contract) reduces the recall duration compared to those workers who were, instead, holding an open-ended contract. For workers with temporary or permanent-per-task contracts in their previous job, the estimated coefficient in the duration part of the SPDM is the most negative. These workers typically enjoy strong links with their previous employer when they are out of work. In addition, when being laid-off, those individuals receive payments subsidized by the Government through the UI system for the time not worked —see Alba et al. (2007) or Arranz and García-Serrano (2011a).

As regards the income of the unemployed, our results show that the level of UI benefits becomes an important determinant of recall unemployment duration, under the SPDM estimation results. In particular, the higher the level of UI benefits, the shorter the recall duration is. This means that an individual with large UI benefit levels will expect recall, so that he may be willing to wait as long as the benefits lapse before searching for another job. That is, these individuals will likely be more selective concerning new job opportunities than those who are receiving a lower level of UI benefits (due to their recall expectation, the former are expected to be less likely to accept a job with a different employer). The risk that a firm loses laid-off workers to alternative employers will therefore be lower if they are receiving large UI benefits. An additional reason for this is the fact that other employers may be unwilling to incur the initial fixed cost of hiring and training workers who have a reasonable prospect of recall. This situation might make a rotating system of layoffs attractive for employers during product demand downturns (see, e.g., Alba et al., 2012).

As regards other variables that, apart from the UI benefit level, may affect unemployed individuals' reservation wages, we find that net wages received in the last job have a significant effect on the length of time until a recall occurs. As can be observed in Table 2, unemployed individuals with higher (lower) net wages in the last job are recalled sooner (later) by their previous employer than the remainder ones[xii]. This finding is consistent with the above-mentioned effect associated with UI benefit levels, since those individuals with larger wages when employed will also be receiving larger UI benefits when unemployed. This result implies that these individuals will show a reduced new job search intensity induced by a larger perceived recall prospect.

Apart from gender, age, job category and the previous type of contract, there are several other variables that provide interesting insights into the time until recall in Spain. One of these variables is *firm size*. Given the costs borne by workers in recalls —in terms of losses in current income, future benefit entitlements, employment security and human capital depreciation during lay-offs— workers' councils (*comités de empresa*), which only exist in firms with at least 50 employees, are expected to minimize the duration of recalls effectively in larger firms (Alba et al., 2012). As firm size increases, there will be more and stronger workers' councils with both the power and the incentive to intervene and assist workers' optimizing behaviour. In contrast, workers laid-off by smaller companies are expected to experience longer recall durations because they will be less able to influence the timing of such recalls. This expectation is confirmed in estimation results provided in table 2. Compared to firms with less than 10 employees, the recall duration of unemployed individuals who were previously employed in firms with more than 50 employees is around 38-39 per cent less. Therefore, duration until a recall occurs is reduced as firm size increases. Other relevant variable that provides interesting insights into the way workers exit unemployment through recall in Spain is their previous employment history. As can be observed in table 2, unemployed workers with less than 6 months of tenure in their previous job are recalled sooner than the remainder individuals. This finding may reflect that fact that recalls are synchronized with the expiration of unemployment benefits, because laying off a worker with a high potential entitlement is less costly to the firm than laying off an equally productive worker with a low potential entitlement (Alba et al., 2012). Finally, compared to individuals in construction, individuals in the remaining industries —except for trade— are significantly more likely to be recalled, particularly those with previous experience in the health industry.

As expected, there are relevant differences between the SPDM and the SDM estimates in table 2, both as regards their magnitude and significance. Some of the variables show undervalued estimated hazard rates in the traditional SDM. This is the case, for instance, of the individuals' nationality: whereas under the SDM non-Spanish unemployed individuals remain unemployed before being recalled about 40 per cent longer than Spanish unemployed workers, under the SPDM estimates the former individuals survive 57 per cent longer than the latter. Differences between estimation results from both models are apparent when we analyze estimated coefficients for the variables collecting the type of contract and job category or skill jobs. Following SDM (SPDM) estimates, workers holding temporary or permanent per task contracts in their previous job are estimated to survive in unemployment 93 (42) per cent less than those holding open ended contracts. As can be observed, job category and industry variables are also highly sensible to the application of each of the econometric models. For example, while Blue Collar (high, medium and low skilled) workers are recalled sooner in the SDM, but they are recalled later in the SPDM. As regards industry variables, and following SPDM estimation results, UI recipients employed in trade are recalled later than those in construction (the former remain 25 per cent longer in unemployment before being recalled than the latter). In contrast, being employed in trade implies a shorter duration in unemployment until a recall occurs under the traditional SDM. In other industries as other services, personal services and housing, a negative significant effect on the recall duration is obtained under the SDM, but no effect is evident under the SPDM estimation results.

Finally, the estimated coefficient of the scaling parameter under the SDM is 0.944 almost equal to 1[xiii], which means that the probability of recall decreases with time. In contrast, the estimated coefficient of the scaling parameter obtained in the SPDM is 0.759 (below 1), which indicates that the probability of being recalled rises with time, but falls after *t* reaches some critical value (as can be observed in figure 6, see below). In particular, the recall hazard rises sharply in the first two months of unemployment and drops quickly after that. Therefore, benefit recipients are most at risk of being recalled when 45 days have passed after entering into insured unemployment. This was the main reason why the log-logistic form was chosen (this functional form allows for a maximum in the probability of being recalled, as suggested by the data).

Further insights into differences between the SPDM and the SDM are illustrated in figures 5 and 6. These figures plot the estimated mean hazard and survival functions, respectively, for each of the models. Figure 5 plots the predicted survival function from the standard duration model (SDM) and the split population duration model (SPDM). The SDM survival estimates begin and remain high, and decline only very slowly. Moreover, although in figure 5 the log-logistic predicted survival function for the SDM should eventually reach 0 (implying that all individuals in the sample will eventually be recalled), the function does not reach 0, which confirms that the model is misspecified (as already commented above). On the contrary, the estimated survival function in the SPDM declines rapidly. Thus, while the SDM estimates a 0.48 probability of an individual remaining unemployed beyond one year, the corresponding probability for the SPDM is only 0.19. Bear in mind, however, that this estimate is conditional on the individual being recalled, itself a separate issue in the model presented here.

[FIGURE 5]

Figure 6 illustrates that the estimated hazard for the SDM is excessively low and exhibits little variation over time, as compared to that from the SPDM. Moreover, the predicted hazard function for the SPDM fits the shape of the Kaplan-Meier estimates shown in figure 1 reasonably well — the recall hazard rises to a peak around 41 days after the individuals' getting unemployed, and then declines monotonically after that. In contrast, the estimated hazard for the standard duration model displays no such non-monotonicity property: the predicted hazard function for the SDM is rather monotonic and does not show the typical peak during the first days of the unemployment spell.

[FIGURE 6]

Summary and conclusions

In this paper, we analyze the driving forces behind the duration pattern of recall unemployment spells in Spain, under the framework of duration models. Specifically, we examine the factors that determine unemployment benefit recipients' duration in UI until a recall occurs, using an administrative dataset from the Spanish MCVL for the period 2005-2010. Our focus is placed, therefore, on the length of time until a recall occurs. The standard assumption in duration models that every individual will eventually exit from unemployment (i.e., that the probability of survival will become zero as time goes to infinity), is not appropriate because a substantial proportion of benefit recipients in our sample does not leave unemployment to return to the same employer. One approach that takes into account the never-recall possibility is the split population model proposed by Schmidt and Witte (1989). Following their approach, we include in the likelihood function a term representing the probability of eventual recall and define the hazard function conditional on eventual leaving. In particular, we estimate two models based on two competing assumptions: the first model takes the standard assumption in duration models that all recipients are eventually recalled to their previous employer. The second one consists of a split-population model which takes into account the possibility that there are some recipients who will never exit unemployment to a recall job. This model allows us to examine the variables that affect the propensity and timing of recall jobs, given that only a proportion of benefit recipients ends their unemployment spell in a recall job.

One of the objectives in estimating the split population model for recalls as an alternative to the standard duration model is to examine how estimation results change when the standard assumption on duration models is relaxed and to analyze which individual characteristics are significantly associated with the recall hazard rate. In determining the length of time prior to the recall outcome, controlling the probability of never being recalled becomes critical in analyzing exit from unemployment via recalls in Spain, because there are important differences in estimation results when the standard assumption on duration models is relaxed. In particular, one important difference between both models relies not so much in the significance of the explanatory variables, but in the magnitude of the estimated hazard rates. For instance, according to the traditional duration model, BCHS, BCMS and BCLS workers are recalled earlier than the WCHS ones. However, results in the SPDM show that those individuals are indeed recalled later than WCHS workers. Hence, once the probability of eventual recall is controlled for, some variables change their estimated signs in the recall hazard function of the split population duration model. In general, the variables that make individuals more likely recalled by their previous employers show undervalued estimated coefficients in the standard duration model. For instance, individuals working in firms with above 250 employees stay unemployed under UI benefits in the standard duration model (split population model) for a period which is 49 (38) per cent shorter than individuals working in other types of firms.

There are four main conclusions deriving from our analysis. First, estimation results on age and individual's qualification show that the accumulation of firm-specific human capital by older workers may serve as an explanation for the observed differences in age-specific transition patterns. The job-shopping behaviour of younger workers and the level of qualifications reveal as good explanatory factors of the probability of escaping UI for recalled workers. Therefore, employers tend not to rehire persons with insufficient firm-specific human capital, given its high cost of acquisition in the open market. Second, the type of contract the unemployed individual held in his/her previous job presents a very strong association with duration until recall: individuals who entered UI from a job with a temporary or permanent-per-task contract have significantly shorter recall duration. As seasonal downturns in demand and production are easily anticipated by employers, this result indicates that they may turn to lay-off workers temporarily as an employment adjustment strategy. Third, the fact that recall duration is shorter the larger the level of UI benefits and the larger the wages received in the previous job suggests that UI is of benefit to the firm because reducing the intensity with which temporarily laid-off workers look for new jobs helps to keep them permanently attached to the firm: the risk of losing training investments the firm has made in these individuals, particularly those with larger levels of specific human capital (which is typically associated with larger wages and UI benefit levels) is, therefore, reduced. Finally, the finding that unemployed workers with less than 6 months of tenure in their previous job are recalled sooner than the remainder individuals, suggests the UI system may be enlarging the incidence of temporary layoff unemployment. In particular, because laying off a worker with a high potential entitlement is less costly to the firm than laying off an equally productive worker with a low potential entitlement, recalls may be synchronized with the expiration of unemployment benefits, particularly of those individuals with shorter entitlement periods. The risk that the employer loses laid-off workers to alternative employers with longer entitlement periods who expect recall is clearly lower. Hence, for individuals with short entitlement periods, the construction of the UI-benefit system may make it possible to work just enough to qualify for new periods of benefit and be unemployed during the rest of the year. This may be an important source of temporary layoffs.

In essence, our study has re-examined and extended previous work on unemployment duration and recalls in the Spanish context. As we have seen, the fact that the majority of UI benefit recipients are not essentially subject to high recall likelihood has important implications for modelling the incidence of those recalls. Our study points out the potential usefulness of split-population models to researchers studying unemployment duration data more generally.

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Table 1. Descriptive statistics of UI benefit recipients by destination states

	CENSORED		NEW JOB		RECALL JOB	
	Mean	S.E.	Mean	S.E.	Mean	S.E.
Gender						
Men	0.483	0.500	0.624	0.484	0.444	0.497
Age groups						
<24 years	0.068	0.252	0.115	0.319	0.057	0.232
24-29 years	0.215	0.411	0.286	0.452	0.203	0.403
30-44 years	0.483	0.500	0.446	0.497	0.504	0.500
>44 years	0.234	0.424	0.154	0.360	0.235	0.424
Nationality (Non-Spanish)	0.095	0.293	0.081	0.272	0.055	0.228
Job Category						
WCHS	0.047	0.211	0.046	0.209	0.105	0.306
WCMS	0.039	0.192	0.042	0.201	0.035	0.184
WCLS	0.254	0.435	0.245	0.430	0.228	0.419
BCHS	0.231	0.422	0.268	0.443	0.230	0.421
BCMS	0.183	0.387	0.170	0.375	0.168	0.374
BCLS	0.247	0.431	0.230	0.421	0.234	0.423
Industry						
Manufact. and energy	0.168	0.374	0.164	0.370	0.146	0.353
Construction	0.117	0.321	0.154	0.361	0.079	0.270
Trade	0.177	0.382	0.165	0.371	0.075	0.264
Hotels and restaurants	0.138	0.345	0.105	0.307	0.150	0.357
Transport	0.051	0.221	0.062	0.241	0.065	0.246
Business activi ies, financial intermediation, real state and renting	0.227	0.419	0.247	0.431	0.211	0.408
Education	0.029	0.167	0.022	0.146	0.058	0.234
Health	0.042	0.202	0.039	0.193	0.176	0.380
Other services, personal services and housing	0.050	0.217	0.042	0.200	0.040	0.197
Firm size						
0	0.354	0.478	0.399	0.490	0.252	0.434
1-9 workers	0.211	0.408	0.187	0.390	0.125	0.331
10-19 workers	0.080	0.271	0.078	0.267	0.064	0.244
20-49 workers	0.100	0.300	0.095	0.294	0.090	0.287
50-249 workers	0.136	0.342	0.128	0.334	0.180	0.384
250+ workers	0.120	0.325	0.112	0.316	0.289	0.453
Contract in previous job						
Open-ended	0.270	0.444	0.203	0.402	0.020	0.140
Temporary & permanent per-task	0.352	0.477	0.393	0.488	0.518	0.500
Casual	0.315	0.465	0.340	0.474	0.229	0.420
Other fixed-term	0.063	0.244	0.065	0.246	0.233	0.423
Tenure in previous job						
< 6 months	0.456	0.498	0.525	0.499	0.617	0.486
≥6 months and <1 year	0.204	0.403	0.196	0.397	0.295	0.456
≥1 year and <3 years	0.225	0.417	0.199	0.399	0.075	0.264
≥3 years	0.116	0.320	0.081	0.273	0.012	0.109
UI level (€/day)	21.912	58.005	24.439	17.924	25.679	10.997
Wages (€/day)	54.405	148 210	47.508	59.551	50.883	131.402
Sample	6,855		26,291		16,994	
Sample (weighted)	171,375		657,275		424,850	

Source: Spain: MCVL 2005-2010.
Notes: 'Job category' is classified as: White-collar high-skilled occupations, WCHS (managers, workers with university degree, technical engineers and qualified assistants); White-collar medium-skilled occupa ions, WCMS (clerical and workshop heads and assistants); White-collar low-skilled occupations, WCLS (administrative officials and other clerical workers); Blue-collar high-skilled occupations, BCHS (first and second class officials); Blue-collar medium-skilled occupations, BCMS (hird class officials and specialists); and Blue-collar low-skilled occupa ions, BCLS (labourers).

Table 2. Standard and split population duration model estimates

	STANDARD LOG-LOGISTIC			SPLIT-POPULATION LOG-LOGISTIC-LOGIT					
	LOG-LOGISTIC DURATION			LOG-LOGISTIC DURATION			LOGIT		
	Coef.	Std. dev.	T-ratio	Coef.	Std. dev.	T-ratio	Coef.	Std. dev.	T-ratio
Gender									
Men	0.319	0.024	***	0.185	0.027	***	-0.422	0.055	***
Women	-	-	-	-	-	-	-	-	-
Age groups									
<24 years	-	-	-	-	-	-	-	-	-
24-29 years	-0.158	0.043	***	-0.176	0.063	***	-0.059	0.124	
30-44 years	-0.571	0.041	***	-0.554	0.060	***	0.052	0.119	
>44 years	-0.684	0.043	***	-0.582	0.062	***	0.305	0.125	***
Nationality (Non-Spanish)	0.334	0.040	***	0.451	0.053	***	0.147	0.115	
Job category									
WCHS	-	-	-	-	-	-	-	-	-
WCMS	0.244	0.065	***	0.411	0.072	***	0.496	0.160	***
WCLS	0.151	0.045	***	0.130	0.049	***	0.154	0.116	
BCHS	-0.162	0.050	***	0.236	0.058	***	1.107	0.133	***
BCMS	-0.167	0.051	***	0.130	0.058	**	0.926	0.135	***
BCLS	-0.126	0.051	**	0.181	0.058	***	0.924	0.132	***
Industry									
Manufact. and energy	-0.691	0.042	***	-0.274	0.056	***	0.746	0.094	***
Construction	-	-	-	-	-	-	-	-	-
Trade	-0.147	0.049	***	0.221	0.066	***	0.649	0.117	***
Hotels and restaurants	-0.732	0.044	***	-0.123	0.059	**	1.359	0.119	***
Transport	-0.989	0.053	***	-0.456	0.075	***	1.129	0.140	***
Business activities, financial intermediation, real state and renting	-0.515	0.039	***	-0.381	0.054	***	0.318	0.085	***
Education	-0.768	0.063	***	-0.187	0.076	***	1.561	0.183	***
Health	-1.708	0.056	***	-1.088	0.082	***	1.407	0.202	***
Other services, personal services and housing	-0.615	0.059	***	0.018	0.077		1.466	0.179	***
Firm size									
0	-0.084	0.032	***	-0.321	0.041	***	-0.438	0.082	***
1-9 workers	-	-	-	-	-	-	-	-	-
10-19 workers	-0.221	0.045	***	-0.241	0.057	***	-0.019	0.118	
20-49 workers	-0.316	0.041	***	-0.459	0.050	***	-0.291	0.101	***
50-249 workers	-0.509	0.035	***	-0.499	0.043	***	0.118	0.092	
250+ workers	-0.675	0.036	***	-0.474	0.044	***	0.729	0.102	***
Contract in previous job									
Open-ended	-	-	-	-	-	-	-	-	-
Temporary & permanent per-task	-2.648	0.065	***	-0.552	0.115	0 000	2.958	0.133	***
Casual	-1.921	0.066	***	-0.166	0.117	0.158	2.264	0.137	***
Other fixed-term	-2.718	0.071	***	-0.274	0.126	0 030	4.025	0.249	***
Tenure in previous job									
< 6 months	-	-	-	-	-	-	-	-	-
≥6 months and <1 year	0.104	0.024	***	0.518	0.033	***	0.946	0.084	***
≥1 year and <3 years	1.039	0.035	***	1.430	0.054	***	0.732	0.135	***
≥3 years	1.392	0.085	***	1.109	0.148	***	-0.230	0.185	
Log(UI level)	-0.620	0.032	***	-0.392	0.035	***	0.427	0.065	***
Log(wages)	-0.275	0.027	***	-0.475	0.036	***	-0.203	0.059	***
Constant	6.935	0.149	***	3.573	0.194	***	-3.938	0.347	***
Shape Parameter: p	0.944	0.006	***	0.759	0.007	***			
Observations		50,140				50,140			
Log-likelihood		-45458.15				-28067.301			

Notes: N=50,140 (16,994 recall observa ions). Predicted eventual recall rate for split population model = 0.3639. We have also included dummy variables for each quarter of exit.

Figure 1. Survival functions. All sample and recall sub-sample

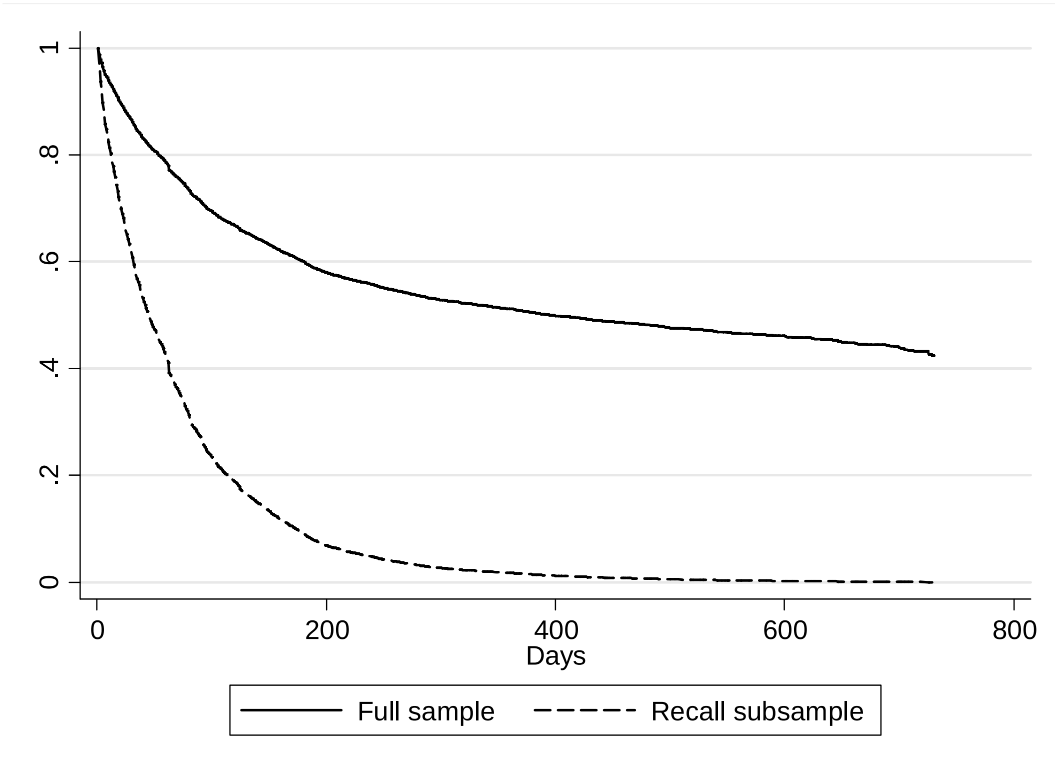


Figure 2. Kaplan Meier Recall hazard function. All sample

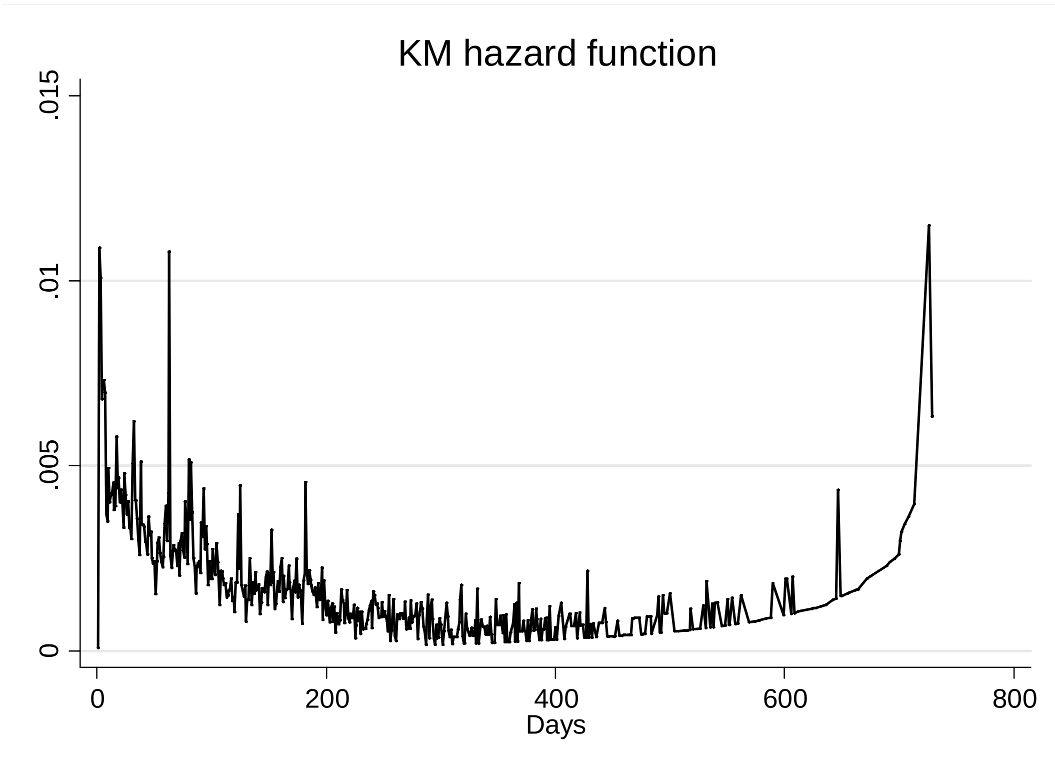


Figure 3. Cumulative Cox-Snell residuals: standard duration model (SDM)

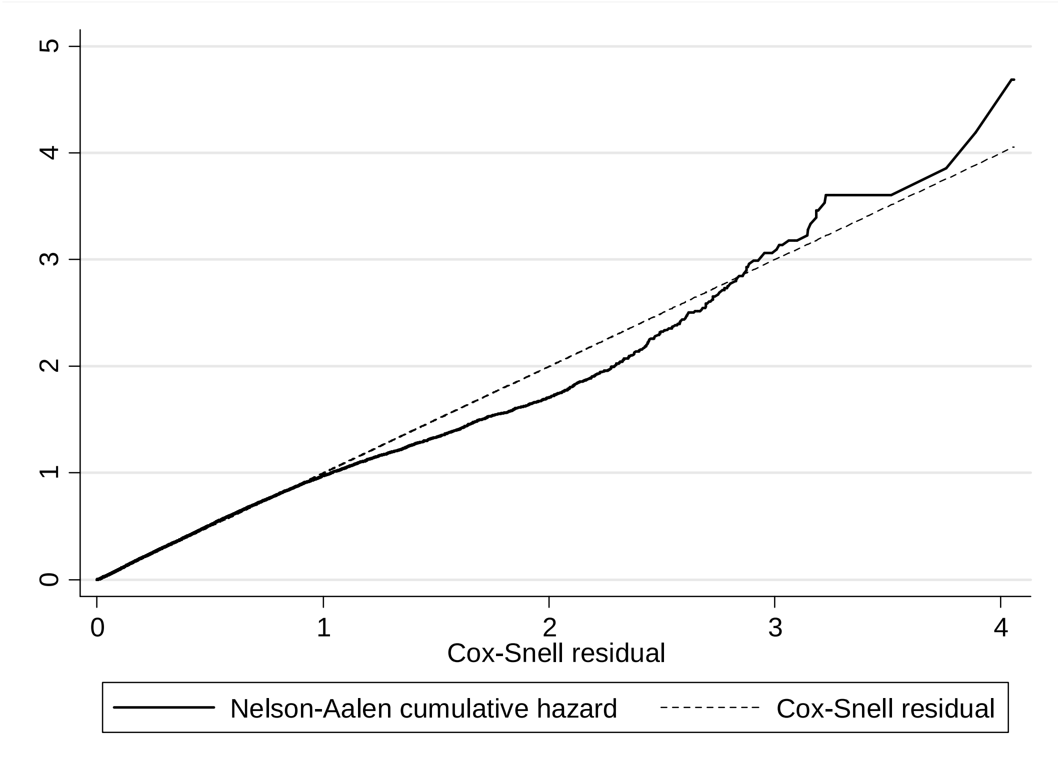


Figure 4. Cumulative Cox-Snell residuals: split-population model (SPDM)

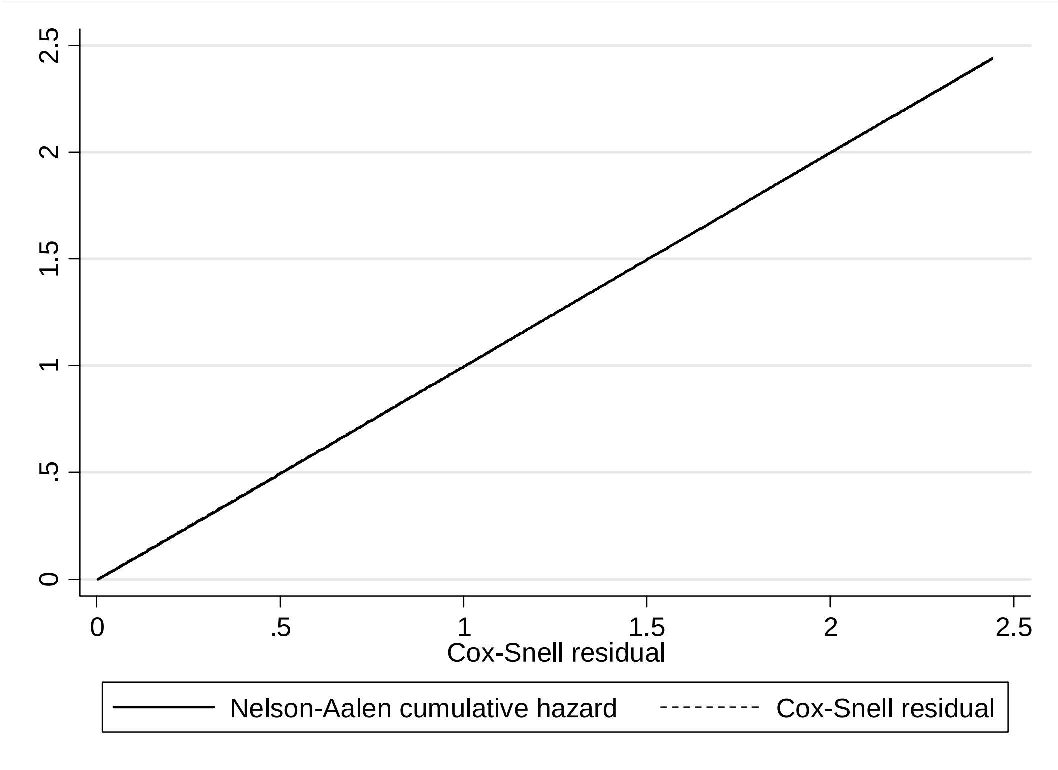


Figure 5. Standard (SDM) and split-population (SPDM) survival estimates

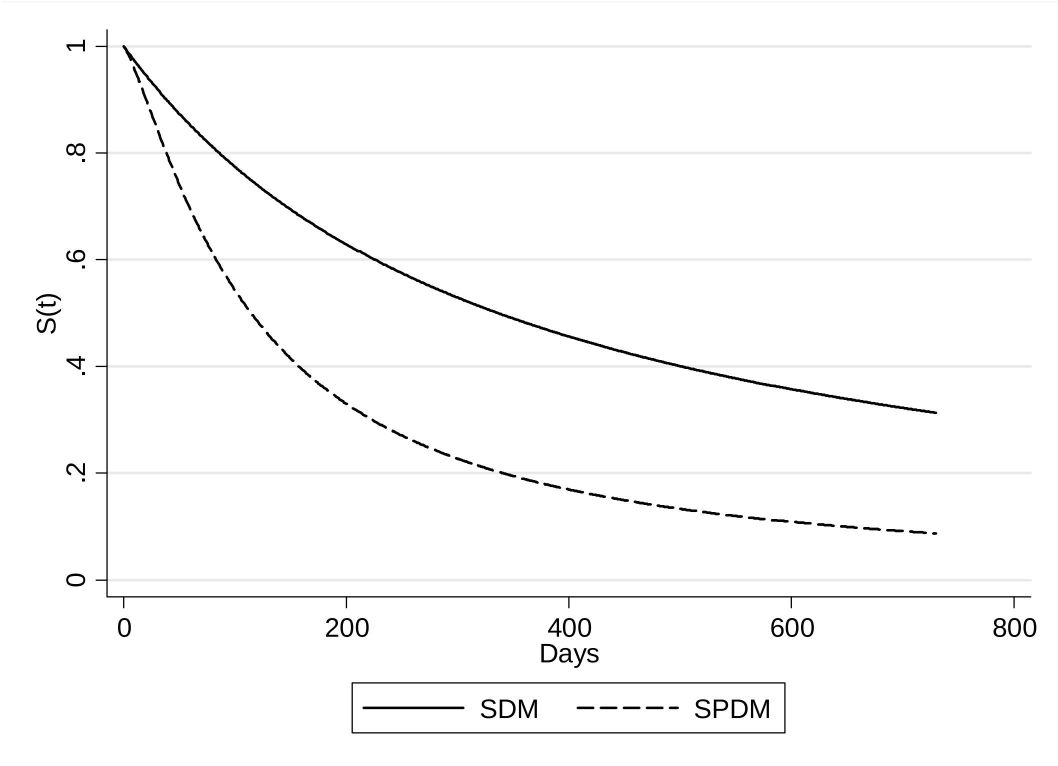
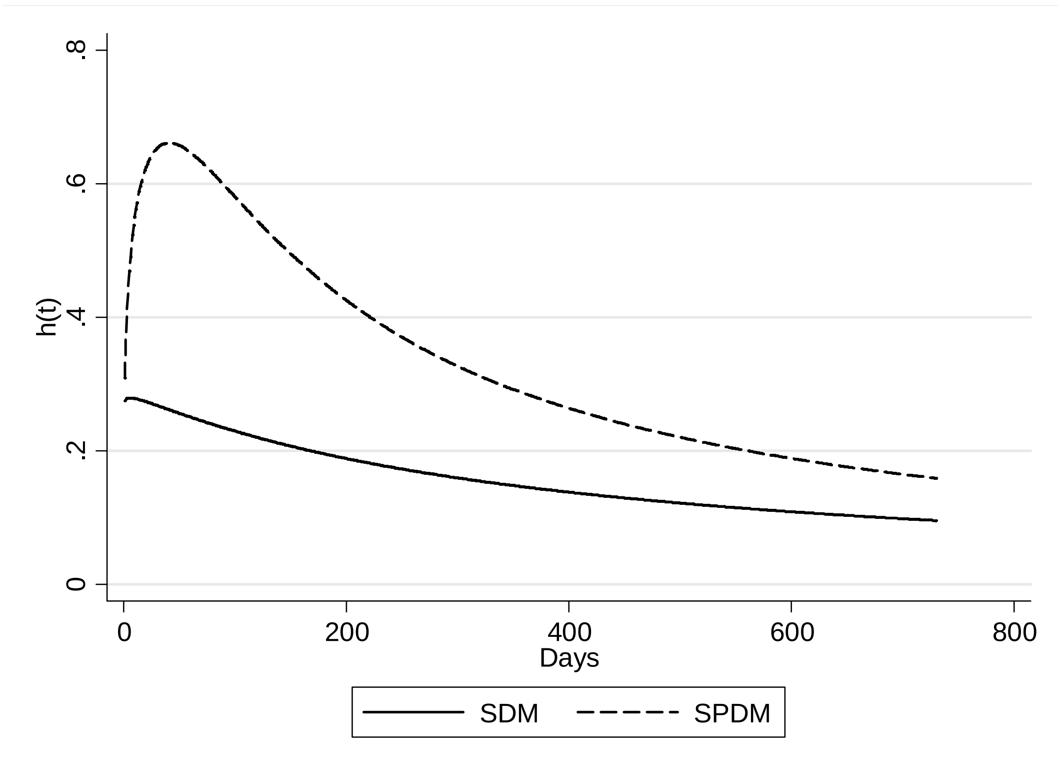


Figure 6. Standard (SDM) and Split-population (SPDM) hazard estimates.



[i] Another notable characteristic of the UCS in Spain, as in other European countries, is the availability of UA for individuals in the following situations: (1) did not meet the minimum contribution period for eligibility; (2) exhausted UI and has family dependents; (3) returned from foreign migration; (4) was released from prison; (5) an invalidity spell ended by the labour authority declaring the worker able to take a job; (6) aged 52 or older. In this paper, we only focus on UI recipients.

[ii] It should be stressed that recall is always just a possibility and never a certainty. Unfortunately, we only refer to temporary lay-offs in an *ex post* sense—i.e., job separations ending in recall. We have no information on *ex ante* temporary lay-offs—i.e., those that begin with a person expecting to be recalled. In any case, this *ex post* concept gives the proportion of unemployment from spells involving no job change (Feldstein, 1975; Clark and Summers, 1979), and it is not ambiguous in the sense that it is not based on whether individuals decide on what is a new employer and what is not (see Alba et al., 2007).

[iii] It is noteworthy that we have no information on *ex ante* temporary layoffs— i.e., those that begin with an individual expecting to be recalled and we only refer to temporary layoffs in an *ex post* sense —i.e., job separations ending in recall.

[iv] Although this dataset does not include information on the entitlement period, it includes information on the previous employment duration, which can be considered as a proxy variable of entitlement duration.

[v] The 'tax module' in the MCVL provided by the Tax Administration National Agency (*Agencia Tributaria*, AEAT) gives annual data on different types of incomes: wages and salaries; pensions; unemployment benefits (in the event a worker is separated from a job and eligible for them); income from economic activities; and others.

[vi] One of the main advantages of the MCVL dataset is that the information contained in the personal, contribution and tax files can be matched thanks to the existence of a unique identification number for each person and employer. Nevertheless, this procedure is not easy. Arranz and García-Serrano (2011b) describe the procedure to compute daily wages and level of benefit from the tax module from the MCVL.

[vii] This model is identified even when the variables in this *logit* or *probit* model are identical to those in the model of duration. This means that one can test for the effects of the same set of variables on both the incidence of failure and the duration associated with it (Schmidt and Witte, 1989).

[viii] Since time dependence in the log-logistic duration model is captured by the estimates of *p* and λ, in our estimations we omit dummies to capture time dependence from the duration part of the model.

[ix] The parameters can be estimated using maximum likelihood estimation procedures in Stata. The programming code used to implement the SPD was created by Foster and Jones (2001) using the "ml max" command in Stata.

[x] In the log-logistic model, the standardized residuals should behave as a sample from a logistic distribution, if the fitted model is correct. Equivalently, the Cox-Snell residuals for the log-logistic accelerated failure time model are given by: $r_{Ci} = -\log\left[1+\exp\left(r_{Si}\right)\right]$, where r_{Si} is the *i-th* standardized residual. This standardized residual is obtained from: $r_s = \ln(t) - \hat{\beta}\,\overline{X}\big/\hat{p}$, where *p* is the scale parameter estimated in the model.

[xi] Regression coefficients obtained in the SPDM are interpreted as in traditional logit and survival analyses: when exponentiated, the logit coefficients are interpretable as odds ratios and the survival analysis coefficients as hazard ratios. In AFT models, a one unit increase in *X* leads to a β increase in the logged survival time. An alternative interpretation is that actual survival times increase at a rate of β or by 100 β per cent with a unit increase in *X*. We can also look at the percentage change in the survival time associated with a change in the value of some covariate, *X,* by some amount δ: Percentage change= 100 (exp(β*δ)-1). If δ is just one unit, we say that one unit increase in X increases the survival time by (exp(β)-1)*100 percent.

[xii] In previous versions of this paper a replacement rate variable was included in the estimations (this variable was calculated by dividing the level of UI benefits during the unemployment period by the individual's net wage in his/her last job). Results showed that the replacement rate did not significantly affect recall unemployment duration.

[xiii] Recall that the scaling parameter estimated in the log-logistic model provides us with information about the shape of the hazard function. If *p*<1, the log-logistic hazard increases and then decreases. If *p*≥1, the hazard is monotone decreasing.