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Re-employment Probabilities for Spanish Men: What Role Does the Unemployment Benefit System Play?

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Abstract

We analyse the re-employment probabilities of almost 330,000 Spanish men aged 20-59 years who began a unemployment insurance (UI) spell between February 1987 and November 1991 using data derived from the national unemployment benefit administration database (SIPRE) and discrete time duration models with flexible baseline hazards. We show: (i) the level of UI benefits has a relatively small disincentive effect on re-employment rates; (ii) re-employment exit hazards increase as UI exhaustion approaches but, again, the effect is relatively small. (iii) Extensions to Unemployment Assistance eligibility lowered re-employment probabilities. Also (iv) there are clear seasonal and cyclical effects on re-employment rates, and (v) rates are much higher for those who enter UI from a fixed-term employment contract rather than permanent one, and (vi) for young workers. These results are consistent with other research drawing attention to the impact on unemployment of inflexibilities in Spanish labour market institutions, combined with low inter-regional mobility and reliance by many for support via their family.

1 May 2000

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1. INTRODUCTION

The relationship between unemployment duration and unemployment benefits is a complex multi-dimensional one. Five main features are highlighted by the findings of earlier micro-econometric research. First, there is the elasticity of unemployment duration with respect to changes in unemployment benefit levels and income replacement rates. There is consensus that higher benefits do have a disincentive effect on unemployment probabilities, but the effect is relatively small on average (see Atkinson and Micklewright, 1991, for a survey). Second, the unemployment income disincentive effect may vary with elapsed unemployment duration. A series of British studies has found no effect for the long-term employed.[1] Third, there is the potential impact of limited duration of eligibility of unemployment insurance (UI). North American research in particular has found that unemployment exit rates rise as benefit exhaustion approaches.[2] Fourth, there is the relationship between unemployment exit rates and elapsed duration ('pure' duration dependence). This has often been found to be non-monotonic, suggesting that it is important to use flexible specifications of the baseline hazard function.[3] Fifth, factors associated with exits from unemployment may differ with the type of exit. For example, researchers have found differences between exits to full-time jobs and exits to other jobs, and between recalls from temporary lay-offs and exits to new jobs.[4]

This paper focuses on the exits from unemployment to a job by Spanish men, and investigates the first four features of the unemployment duration-benefit relationship cited. The impacts of seasonal and business cycle effects (less commonly studied in previous work) are also examined. We also draw attention to the relevance of Unemployment Assistance (UA) benefits for assessing the impact of Unemployment Insurance (UI).

Spain has a serious unemployment problem, the worst of all OECD countries (Dolado and Jimeno, 1997). In the early 1970s the Spanish unemployment rate was about the same as the OECD and EU average, about 5%, but increased dramatically to reach 21% in 1985. After this peak the rate declined until the beginning of the 1990s, but then increased sharply again, from 16% to reach 24% in 1994. These figures refer to the combined rate for men and women. The trends for men alone are similar: see Figure 1. Although the cyclical pattern for Spanish unemployment is the same as the EU's, Spanish unemployment rates have been about double the EU average rate since about 1980. Spain is also distinctive in the nature of its unemployment, being a 'low flow, high duration' country (Layard, Nickell and Jackman, 1991, chapter 5). Increases in its unemployment rate are more closely related to increases in unemployment duration than to increases in inflows: see Figure 1. Hence the particular importance of modelling unemployment exit rates for understanding Spanish unemployment levels. Our data cover 1987-93 and so we cannot use them to explain the sharp rise in unemployment prior to 1985, but we can contribute to understanding of its persistence thereafter.

<Figure 1 near here>

The contribution of this paper derives from the availability of a rich new longitudinal data set derived by record linkage from the Spanish national Integrated Benefits System

[1] See Narendranathan and Nickell (1989), Narendranathan, Nickell and Stern (1989), Narendranathan and Stewart (1993b, 1995) and Nickell (1979a, b).

[2] See Bratberg and Vaage (2000, Norway), Ham and Rea (1987, Canada), Katz and Meyer (1990a, USA), Lindeboom and Theeuwes (1993, Netherlands), Meyer (1990, USA), Micklewright and Nagy (1996, Hungary), Moffitt (1985, USA), and Winter-Ebmer (1998, Austria).

[3] See, for example, Meyer (1990) and Narendranathan and Stewart (1993a). These papers also show that the estimated impacts of UI were relatively robust to whether or not allowance was made for unobserved heterogeneity, given the use of a fully flexible baseline hazard function. A similar robustness result is reported by Dolton and van der Klaauw (1995) in their study of exit rates from teaching.

[4] See Narendranathan and Stewart (1993a) and Katz and Meyer (1990b), respectively.

administrative database (*Sistema Integral de Prestaciones*, SIPRE). Fifteen cohorts of persons beginning spells of UI receipt in the February, June and November of each year between 1987 and 1991 have been followed until either exit from UI receipt or exhaustion of entitlement up to two years later.[5] We use information about almost 330,000 unemployment spells for men. The advantages and disadvantages of the SIPRE are discussed in some detail later; for the moment it suffices to draw attention to a few features. In particular the SIPRE is similar to the unemployment administrative record data sets used in earlier research (see footnote 2 for citations), though is very much larger. It is the only Spanish source with information about UI eligibility and previous earnings. Also the pooled SIPRE data cover almost one full business cycle from peak to peak, so that cyclical and seasonal factors can also be examined. This temporal coverage also introduces exogenous variation in benefits which facilitates identification of potential disincentive effects. One limitation of the data set is that it covers UI recipients rather all the unemployed. Since UI receipt is conditional on having some work experience (see later for details), we cannot describe well the experience of new entrants to the labour force or those with the highest turnover rates.

In Section 2, we briefly outline the search theoretic model and econometric methods which underpin our analysis. We describe the Spanish unemployment benefit system and the SIPRE data base and the variables which we derive from it in section 3. Our analysis of re-employment hazard rates using hazard regressions is reported in section 4, and section 5 provides concluding comments. An Appendix provides supplementary tables and figures.

We find that the level of UI benefits has a relatively small disincentive effect on re-employment rates on average. It is higher for the recently unemployed but negligible for the long-term unemployed. Re-employment exit hazards increase as UI exhaustion approaches but, again, the effect is relatively small. The total re-employment hazard (elapsed duration incorporating time-to-exhaustion) is therefore very similar in shape to the baseline hazard holding eligibility constant: it rises over the first four months of a UI spell and then declines over the following 20 months. Extensions in UA eligibility in 1989 are associated with lower re-employment rates. There are also clear seasonal and cyclical effects on re-employment rates, and rates are much higher for those who entered UI from a fixed-term employment contract rather than permanent one, and for younger workers relative to older workers. These results are consistent with other research drawing attention to the impact on unemployment of inflexibilities in Spanish labour market institutions, combined with low inter-regional mobility and reliance by many for support via their family.

2. MODELLING FRAMEWORK

The dependent variable in our empirical analysis is the monthly re-employment hazard rate, h_{it}, i.e. the conditional probability that a current UI recipient i finds another job during month t, conditional on having remained unemployed up until the end of month t-1. This can be thought of as the product of the probability that he receives a job offer, p_{it}, and the probability that the job offered is acceptable to him, q_{it}.

2.1 Theoretical framework

Standard job search theory provides a useful framework for discussion of the factors influencing these probabilities. In Mortensen's (1977) dynamic stationary search model, for example, each individual maximises the present value of his expected utility, where utility depends on consumption and leisure (there is no saving). There is a fixed wage offer

[5] SIPRE data have also been used by Cebrián et al. (1996) and García Serrano (1997). However both these studies focused on a single cohort of UI entrants, that of June 1990.

distribution, and a constant arrival rate of job offers for given search intensity, s_i. In-work income is equal to the (expected) wage, and out-of-work income equals the unemployment benefit. However benefits are paid only for a fixed duration, and eligibility is conditional on having work experience (new entrants to the labour force or those quitting jobs voluntarily are not eligible). Individuals choose search intensity—which influences the job offer probability—and a reservation wage, w_i with cumulative distribution $F(w_i)$, which characterises the minimum acceptable offer. Mortensen demonstrates that the re-employment hazard rate is proportional to $s_i[1-F(w_i)]$. The hazard h_{it} rises with either increases in search intensity (a rise in offer rate p_{it}) or decreases in the reservation wage (a rise in acceptance rate q_{it}).

The model implies, first, that the hazard rises the closer one is to benefit exhaustion, because s_i increases and w_i decreases.[6] (After exhaustion the hazard is then constant, because the economic environment does not change.) Second, increases in the relative generosity of UI have a two-fold impact, because not only do they raise the utility of remaining unemployed currently, but they also increase the value of future unemployment spells. The former factor has the conventional disincentive effect: the increase in utility of unemployment decreases the hazard rate (assuming consumption and leisure are complements). The latter factor gives rise to a potential 'entitlement effect': a rise in the hazard rate for those with any current benefit entitlement or entitled workers close to exhaustion. (But this is likely to be of second-order magnitude, given discounting of the future.)

Models like Mortensen's are informative about the factors associated with differences between individuals in unemployment outflow rates at a point in time. In particular hazards will be higher for persons with relatively high expected in-work incomes compared to out-of-work income, and also vary with differences in leisure-consumption preference, discount rates, etc. And differences in labour market tightness will also play a role (via offer rate p_{it}).

Although the Mortensen model also provides a clear prediction for each person of a hazard rising with duration, various 'real world' complications suggest one should be cautious about pre-judging the shape of the hazard over time. First there are various non-stationarities. Labour market tightness can vary over the unemployment spell, by locality, by season and with the business cycle. On the one hand, one might expect greater availability of jobs, and thence more job offers, to increase the re-employment hazard. On the other hand, if workers expect continuing future growth in job availability with the business cycle, they may become more choosy about currently available positions.

Benefits may also vary over the spell: for example in Spain, UI payments decline with duration (see below). And the longer the unemployment spell is, the more likely it is that individuals will have run down savings and other resources which might be used for job search, so that search intensity may decline over time. Employers may use long-term unemployment as a signal of unfavourable worker capabilities, implying a decline in the job offer probability with duration. The offer probability may also decline with duration if the worker's human capital depreciates the longer the time out of work. Job acceptance probabilities may decline with duration if the receipt of benefits per se engenders further dependence on them (along the lines of arguments of writers from the Right such as Charles Murray).

Unemployment assistance (UA) benefits for those ineligible for UI or who have exhausted their entitlement also complicate predictions about the re-employment hazard (and are not incorporated in formal models). Payments are typically made at a lower rate than UI

[6] The reservation wage falls as entitlement runs out because the relative utility of unemployment declines. This decline raises the return to extra search and so raises optimal search intensity.

and conditional on a family means test. The length of entitlements also differs from UI. One might suppose that the higher the UA payment or the longer the entitlement, the higher the reservation wage and the lower the hazard, with the size of the effect depending on the generosity of UA relative to both potential in-work income and UI, and differences in preferences for income and leisure. One might also expect the existence of UA to affect the shape of the re-employment hazard during UI receipt, especially close to the time of exhaustion of UI. For example, the hazard might fall as exhaustion approached if UA receipt is anticipated (rather than rise as predicted in the Mortensen model).

In sum, the search framework suggests that re-employment hazards should be modelled in empirical work as a function of expected in-work incomes, out-of-work incomes of different types and duration, personal characteristics associated with differences in search intensity, reservation wages, and factors associated with differences in offer probabilities, including the availability of jobs. Given the ambiguities about the predicted nature of the duration dependence in the hazard, it is important not to place restrictions on the shape of the baseline hazard a priori.

2.2 Empirical modelling framework

In this paper we follow most of the previous literature and model the re-employment hazard using a reduced-form specification.[7] Models are fitted by maximum likelihood methods, with the log likelihood function specified in the following manner.

The probability of observing an incomplete spell of length d_i months for person i is given by the discrete survivor function

$$\prod_{j=1}^{d_i}(1-h_{ij}) \tag{1}$$

and the probability of observing a completed spell of length d_i months is given by

$$h_{id_i}\prod_{j=1}^{d_i-1}(1-h_{ij})\,. \tag{2}$$

Hence one can write the log-likelihood for a sample of n persons as

$$\sum_{i=1}^{n} c_i \ln[h_{id_i}/(1-h_{id_i})] + \sum_{i=1}^{n}\sum_{j=1}^{d_i} \ln\left(1-h_{ij}\right) \tag{3}$$

where c_i is an indicator variable equal to 1 if person i's spell is completed and equal to 0 if it is censored. If one defines an indicator variable y_{it} = 1 if person i gets a job in month t, and y_{it} = 0 otherwise, then the log-likelihood in (3) can be re-written as:

$$\sum_{i=1}^{n}\sum_{j=1}^{d_i}\left\{y_{ij}\ln h_{ij} + (1-y_{ij})\ln(1-h_{ij})\right\}\,. \tag{4}$$

This expression has the same form as the log-likelihood function for regression analysis of a binary dependent variable, in this case y_{it}, and where the unit of observation is now the person-month rather than the person. Thus one can estimate the model using standard software applied to a re-organised data set in which each person contributes as many 'data rows' as he is observed at risk of exit from UI (Allison, 1981; Jenkins, 1995).

We parameterise the discrete monthly re-employment hazard for person i in month t as

[7] Cf. the structural model of, for example, Narendranathan and Nickell (1989). But see also Atkinson and Micklewright who argue persuasively that 'reduced form models provide a much greater degree of flexibility which can be used to handle important institutional details of benefit systems (1991, p. 1708).

$$h_{it} = 1/(1+\exp[-(x_{it}'\beta + \gamma_t)]), \tag{5}$$

where x_{it} is a vector of independent covariates which potentially vary with time (calendar time or duration)—discussed in detail in the next section—and β is a vector of parameters to be estimated. No restrictions are placed on the shape of the baseline hazard: it can take on different values, as summarised by month-specific parameter γ_t. Later we also introduce interactions between covariates and duration, using a specification of form

$$h_{it} = 1/(1+\exp[-(x_{it}'\beta + z_{it}'\iota\, \gamma_t)]), \tag{6}$$

where z_{it} includes a constant term and a subset of the covariates in x_{it}, and ι is a vector of ones of the same length as z_{it}.

Equations 5 and 6 are logistic hazard specifications, and have been used before by, for example, Nickell (1979), Narendranathan and Stewart (1993b), and Bover et al. (1998). We choose it primarily because it makes estimation feasible using our very large data set.

A popular alternative specification for the hazard is the complementary log-log one, yielding a model which is the discrete time representation of the continuous-time proportional hazards model (Prentice and Gloeckler, 1978; Meyer, 1990). Because h_{it} is relatively small in practice, the logistic specification provides a very close approximation to this alternative model.[8] That is,

$$\ln(h_{it}) \approx x_{it}'\beta + \gamma_t \tag{7}$$

to a close approximation. Thus absolute differences in x imply proportional shifts in the hazard, and the estimated coefficient on a covariate which is measured in logarithms may be interpreted as the elasticity of the hazard with respect to that variable. The monthly sequence of values for γ_t characterise the baseline hazard function common to all persons.

We also estimated some models incorporating either a Gamma mixture distribution (Meyer, 1990, as implemented in Jenkins, 1997), or a Normal mixture distribution. We never found the heterogeneity variance to be statistically significant, and all other parameter estimates were very similar to the corresponding ones in models excluding unobserved heterogeneity. (Bover et al. (1998) also found that the re-employment hazard rates in Spain changed little in a model which controlled for unobserved heterogeneity.) Moreover estimation routines of the mixture models required about a week to converge. We therefore concentrate on the models without unobserved heterogeneity.

3. THE SPANISH UNEMPLOYMENT BENEFIT SYSTEM AND THE SIPRE DATA

There are two types of unemployment benefit in Spain: unemployment insurance (*Sistema contributivo*) and unemployment assistance (*Sistema asistencial*). The regulations were changed for those entering unemployment in 1992 and thereafter.[9] The post-1992 UI rules do not apply to our sample (the latest cohort entered UI in November 1991). However changes in UA over the period were relevant to many in the sample, and we would expect it to affect their re-employment behaviour.

3.1 Unemployment insurance (UI, pre-1992 system)

UI was paid to employees (excluding civil servants and domestic workers) who did not quit their job voluntarily, and who have paid a minimum number of contributions. Contributions for at least 6 months over the last 48 months were required for eligibility.

[8] This was verified in preliminary analysis. All estimates were derived using Stata 6.0 on a Unix Sun Solaris workstation with 750mb RAM installed. Estimation of the logistic models took between 40 and 120 minutes (depending on the number of covariates), whereas estimation of each proportional hazards cloglog model took about one day.

[9] Our description is compiled from Blanchard et al. (1995), Bover et al. (1998), Cebrián et al. (1996), and Toharia (1997).

Length of entitlement depended on the number of months contribution made, according to a schedule shown in Table 1.

The amount of UI paid was equal to a fraction π of the average of the 'regulatory base' in the last six months prior to unemployment, where the 'regulatory base' is the gross earnings used to calculate UI contributions. UI receipts were exempt from income tax (until 1994). UI payments decline the longer the unemployment spell is: pre-1992, π equalled 80% during months 1-6 of UI receipt, 70% during months 7-12, and 60% thereafter. Payments were also subject to a minimum amount equal to the statutory minimum wage (SMW)—i.e. about 40% of the average wage—and a maximum amount which varied with the number of children the unemployed person had. The maximum was 1.7×SMW for those with no dependent children, 1.9×SMW with one dependent child, and 2.1×SMW with two or more dependent children.[10]

<Table 1 near here>

These rules imply that after-tax earnings replacement rates may be higher than 80% for people who entered unemployment from jobs with low earnings (up to 100% for those who earned the SMW). After-tax earnings replacement rates are lower than this for those entering unemployment from relatively high earning jobs (above about 2.5×SMW). The floors and ceilings in the payments introduce variation in benefits which is independent of variations in earnings. We exploit this to help identify benefit level effects in our modelling (see below).

3.2 Unemployment assistance (UA)

Two types of worker were eligible for UA. The first group—not members of our sample, by definition—comprised unemployed workers with more than 3 but fewer than 6 months of UI contributions (cf. Table 1). The second and larger group comprised those who had exhausted their UI entitlements. (Between about 25% and 30% of UI entrants exhaust their UI and go on to receive UA—see Table 2 below). Potential UA recipients were also required to satisfy two conditions: (i) per capita family income could not exceed the SMW (75% of the SMW from 1993); and (ii) they had to have 'family responsibilities', a rather broad concept extending to include any relative 'of the second degree'. For example the beneficiary's parents could be included (though, in 1993, the definition was restricted to cover just a spouse and dependent children, if present). UA was paid at a rate of 75% of the SMW, generally for up to six months, renewable up to 18 months, depending on work experience.

There were three special cases of potential UA recipient relevant to our analysis. First, unemployed workers over the age of 52 or older who met all the requirements for retirement pension receipt were eligible to receive UA until retirement age. Hence arguably a finding that re-employment probabilities for this group are lower than for younger men may be (in part) interpreted as a UA disincentive effect. Second, casual agricultural workers in Andalucía and Extremadura were eligible for a special scheme under which UA-days were paid according to the number of minimum contribution-days made (above a minimum). We

[10] The main changes to the UI system rules since 1992 have been an increase in the minimum contribution period and change in the duration of entitlement. A minimum of 12 months contributions during the previous 72 months is now required (rather than 6 in 48). The duration of entitlement is now equal to twice the modulus of the number of contribution months divided by 6, up to maximum of 24, i.e. the potential entitlement periods are 4,6,8,10,...,24 (rather than 3,6,9,...,24 as before). The fraction π is now reduced to 70% over months 1-6 of UI receipt; and is 60% thereafter. In 1994, UI was made subject to tax, and the minimum payment reduced to 75% of SMW unless the beneficiary has dependent children in which case it remains 100% of SMW. Prior to 1992, social security contributions were paid to UI recipients to enable them to accrue retirement pension rights; since 1994 the unemployed have paid a small fraction of these contributions.

cannot identify this effect directly with our data set. (UA eligibility is not observed.) Third, UA eligibility was extended in 1989 for workers over 45 (see Bover et al 1998, Table A2 p39). We use a time-dependent variable interacting age and date in our models to capture the effect, expecting the extension of eligibility to lower re-employment probabilities.

3.3 The Spanish unemployment benefit system: assessment

Over the period this paper is concerned with, the Spanish UI system was relatively generous in absolute terms (though generosity clearly falls with duration), and UA is less generous than UI. UI in Spain also appears to have been relatively generous relative to other EU and OECD countries. This is suggested by the cross-country analysis by the OECD (1991) of gross replacement rates for 'average production worker levels of 1988 earnings' for a new entrant to UI. Of the countries considered, only Denmark, Sweden and the Netherlands had similar or higher rates to Spain (OECD, 1991, p. 201). Spanish UI coverage is also good from a cross-national perspective: Blanchard et al. report that 'along with France, Holland, Belgium and Germany, Spain had the highest gross coverage rate in the EU in 1992' (1995, p. 135).[11]

Another relevant factor is the relatively non-stringent requirements for job search during UI spells. Signing-on to confirm unemployment status is required in person, but only every 3 months (OECD, 1991, p. 214). Blanchard et al. state also that 'individuals that repeatedly turn down [job] offers retain their rights to continue to continue claiming unemployment benefits, which clearly acts as a disincentive for leaving unemployment' (1995, p. 135). This is plausible, though arguably both features of the UI system may also be a response to prolonged high unemployment rather than a cause.

4. THE SIPRE DATA AND VARIABLE DEFINITIONS

4.1 The SIPRE data

The data we use were produced by the public agency which administers the payment of unemployment benefits, the National Institute of Employment (Insitututo Nacional de Empleo, INEM). Computerisation of their records has enabled longitudinal linkage of records from monthly payroll computer files for all fully unemployed workers (men and women), as well as some others, for example on short-time working. At present, and a reflection of the administrative purposes for which the SIPRE was designed, one cannot easily derive for each unemployed person a complete history containing all spells of UI and UA. The data set available to us contains information about one UI spell per 'fully unemployed' beneficiary (data for the workers who entered the database because of temporary layoff or short-time working were not available).[12]

More specifically, the data comprise fifteen 40% random samples of all the fully unemployed persons who began a UI spell in each of February, June, and November during the five years 1987-1991 inclusive. The data may, in principle, contain multiple spells for the

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[11] Toharia (1997) provides more information about coverage using both benefit administration and labour force survey data. For the period considered in this paper, 1987-1993, Toharia shows that there was a distinct increase in coverage for both men and women. For example, the number of men receiving unemployment benefits (either UI or UA) expressed as a proportion of all unemployed men with work experience (i.e. those eligible for unemployment benefits), rose from about 37% in 1987 to about 47% in 1992 (Toharia, 1997, p. 159). Coverage peaked in 1992, and declined to 1987 levels by 1996.

[12] These and other extracts from the SIPRE data were originally derived for a team at the Universidad de Alcalá to which García-Serrano belongs.

same person, though we cannot observe this from the data. (The chances of this occurring are reduced by the work experience requirement for UI eligibility.)

The variables which are available directly from the administrative records are:

- *Personal data*: sex and date of birth, number of children, whether the claimant has 'family responsibilities' (as defined above), and the autonomous region where the benefit is paid (a close proxy for place of residence).
- *Last job*: the 'regulatory base' (former earnings, as defined above), contribution period, former job type.
- *Benefits*: type of benefit (UI in this case), dates of claim start and end, eligible entitlement period, elapsed duration of current receipt (in days), the reason for entering unemployment, and the reason for exiting the system.

Some variables which we would like to have are not collected, for example, educational attainments (though there are some elements of this in 'former job type'), marital status, and more details about the last job such as industry, firm size etc., or redundancy payments received (which might be used to subsidise job search or self-employment) but, on the other hand, their receipt is likely to be captured by the fixed-term contracts indicator variable.

Our analysis sub-sample comprises men aged 20-59 years with consistent non-missing data on regression covariates. The lower age limit aims at excluding young people just starting their work careers who may also be making educational choices, and the maximum age limit aims at excluding those whose decisions may be influenced by retirement considerations. We defer the analysis of women's unemployment duration to another paper. Our sub-sample excludes men with benefit data containing obvious measurement errors (for example elapsed durations or entitlements inconsistent with the UI rules described above). Those with missing data on covariates were also excluded. All these exclusions removed a maximum of about 1% of each entry cohort.

Our analysis focuses on exits from UI to a job, and treats spells which end because of exhaustion of entitlement or because of exit from UI for 'other reasons', as censored. These other reasons are diverse and include death, retirement, permanent disability, emigration, and self-employment start-ups subsidised with UI. The UI spells which end in exhaustion can also be distinguished according to whether they were followed by a spell of UA or not. It is not possible to identify ex ante those who are potentially eligible for UA.

Subsample numbers and breakdowns by entry cohort and type of exit are shown in Table 2. The pooled sample consists of 329,947 spells, of which 27% ended because of exit to a job. This proportion is much smaller than the fraction of spells ending because of exhaustion of entitlement, about 59%. Of these, just under half the UI recipients went on to receive UA after UI.[13] About 14% of all UI spells for 'other' reasons.

The breakdowns by entry cohort reveal some interesting time-series patterns. November entry cohorts are much more likely to exhaust their UI and not to go on to UA, relative to other entry cohorts. They have correspondingly low proportions in the exit for 'other reasons' group, with the exception of 1991 when this category is relatively large for the February and June cohorts as well.

Interesting time-series patterns in unemployment inflows are also revealed by Table 2 (recall the data represent a large sample from the inflow). Reflecting seasonal factors, the November samples are about 50% larger than the February and June ones in each of the five

[13] How do those without UA survive financially? The most obvious answer is: by dependence on income sharing within their family. Robinson (1997) puts it more bluntly in his subtitle: 'Spain's welfare system is let off the hook by the family'. The incidence of single-person households in Spain is below the OECD average, and most unemployed people live in household with at least one employed person. Spain remains the home of the 'male breadwinner' model, with relatively low labour force participation rates by wives, and a high proportion of young adults living at home (and often unemployed).

years. This pattern occurs within an upward trend in inflows over the whole period (consistent with Figure 1 which shows second quarter inflows over a longer period).

<Table 2 near here>

4.2 Derived variables

Many of the variables we use in the multivariate modelling are listed in Table 3, together with summary statistics.

<Table 3 near here>

Exits to a job are observed in about 4% of the 2,397,685 person-months observed for our sample. (This figure is the mean of variable y_{it} in equation 4, the dependent variable in the regression modelling.) Average UI spell length is 7.3 months and average entitlement is 9.6 months. In fact 41% of the sample were entitled to three months UI, 16% to 6 months, 9% to 9 months, 7% to 12 months, 5% to 15 months, 6% to 18 months, 5% to 21 months, and 13% to the maximum of 24 months.

Turning now to the explanatory variables, we control for age at the start of the UI spell using a non-linear specification, distinguishing seven age groups. Average age is 33 years. In particular we distinguish those aged 52 or more (some 9% of the sample) given the association between UA eligibility and age discussed earlier. About 40% of the sample have family responsibilities (defined earlier).[14]

Former job type is an administrative definition of the UI recipient's former occupation, though it also includes elements related to qualifications. Almost 80% of our UI entrants come from production jobs, about 16% from clerical jobs, and only 6% from degree or higher technical jobs. The large representation of production is largely because risks of unemployment entry are lower for non-production jobs.

A notable feature of the Spanish labour market is the prevalence of fixed-term employment contracts. These contracts were introduced in 1984 in order to improve labour market flexibility and imply lower firing costs (redundancy payments are lower than for 'permanent jobs'). The legislated minimum contract duration was 6 months, and the maximum 3 years. The use of fixed term contracts spread rapidly: 'Between 1986 and 1990, 80% of all contracts registered at employment offices were fixed-term. By 1991, fixed-term and temporary employment accounted for nearly a third ... of total employment' (Blanchard et al. 1995, p. 128). See also Alba-Ramírez (1998). These jobs are held disproportionately by women, youths, and those working in construction, agriculture, retail and hotel/restaurant services. We distinguish men whose last job before the UI spell was covered a fixed term employment contract. They comprise more than four-fifths (84%) of our sample (a fraction consistent with the high proportion of men with relatively short UI entitlements).

To measure differences across persons and over time in labour market tightness we have merged into the data set information about the quarterly all-persons unemployment rate for each of the 17 Spanish autonomous regions over the period covered by our data, i.e. 1987:1-1993:4. A time-series graph of these data (not shown) shows that the rates for each region follow a shallow U-shape, but differences between regions in the level of unemployment are large. For example, in 1987:1 the rates ranged from 30% in Andalucía (a poor southern region) to about 14% in La Rioja and Cataluña. Rates subsequently fell and were about 5 percentage points lower in most regions by the first half of 1991, but then increased to reach 1987 levels again by 1993:4. As we shall show, there are difficulties in identifying an unemployment effect separately from any region effect because the unemployment rankings of the regions are rather stable—a feature emphasised by Jimeno and

[14] We used 'number of children' as a covariate in preliminary analysis and it was never statistically significant given the inclusion of the family responsibilities variable. We therefore excluded it from all later models.

Bentolila (1998) who draw attention to persistence in regional wages, participation rates and real wage inflexibility.

We concentrate on models which include regional fixed effects, to allow for the potential impact of other factors factors besides unemployment. In particular recall that UA eligibility differs by region (there is a special scheme for Andalucía and Extremadura). We also introduce an interaction term between residence in these two regions and UI benefits. These regions stand out as being particularly poor and having high unemployment rates. In such a situation, any job offer is likely to be accepted, so that re-employment probabilities are likely to be relatively insensitive to variations in benefits.

We include a direct measure of the business cycle, namely the quarterly growth rate of GDP (following Bover et al., 1998). Seasonal effects are captured by a set of dummy variables which indicate whether a spell month is in spring (March-May), summer (June-August), autumn (September-November) or winter (December-February). We use a definition of season based on climate, rather than the conventional time-series one based on the calendar year quarter, because we believe our formulation better reflects patterns of hiring in the Spanish labour market. We also include year indicator variables to pick up any other period effects which are not already accounted for the GDP growth, regional unemployment and seasonal variables. They may also pick some effects of the changes to UA in 1993.

Our measure of the in-work income a worker could expect to get if he took a job is the net wage per month from the last job. Use of this definition is common practice in studies based on administrative record data (see e.g. Meyer 1990). Although it has some disadvantages, it is the only measure we have or could feasibly derive.[15] We estimate net wages from the gross wage ('regulatory base') information on the files by applying the tax rates applicable for a single person. (This is justifiable since Spain has an independent taxation system.) Figures were converted to February 1997 prices using the monthly retail price index.

A particular strength of the SIPRE data is the information about UI eligibility. Given the rules of the UI system, we calculated the amount due in each month of the spell (recall UI payments vary with duration). The resulting figures were then converted to February 1997 prices using the monthly retail price index.

Real net wages and benefits were used (in log form) as separate regressors rather than assuming a priori that it was their ratio, the replacement rate, which was the relevant covariate. Nonetheless it is convenient to summarise the relative generosity of the UI system in terms of replacement rates. On average, gross replacement rates were 78% in the first 6 months of the spell, 67% in months 7-12, and 65% thereafter (see Table 3). Average net replacement rates (i.e. adjusting for taxes) are quite a lot higher: 92%, 79% and 75% respectively. It is also important to note that there is substantial variation about these average figures.

Identification of UI benefit level effects separately from wage effects is possible even though UI receipts are related to previous earnings (given the rules described earlier). There are two potential sources of variation providing identification in addition to the usual functional form ones. First the proportionate relationship between earnings and benefits does

[15] Narendranathan and Stewart have argued that such a measure has 'serious disadvantages, including its potential endogeneity. The individuals who are more selective about selecting jobs may have had higher than average earnings' (1993a, p. 72; see also Nickell, 1979, p. 1252). They follow Narendranathan, Nickell and Stern (1989) in using a measure derived assuming that workers concentrate job search on one of 5 labour market segments defined in terms of broad occupational groups. Expected net earnings are imputed as the wage predicted from an occupation-specific wage regression which controls for differences in education and age, fitted to the data of previous earnings. Total net income is then calculated at imputed net earnings plus income from other sources. We do not have sufficient information to be able to implement this procedure.

not apply below the UI payment floor or above the UI payment ceiling. These bounds are relatively wide, however, and so the number of workers outside the cut-offs is not large. We would therefore emphasise the separate time-series variation in each of the two series as a second source of identification. (This particular advantage comes only from pooling the entry cohorts rather than using them separately.)

We analyse the impact of time-to-exhaustion effects in the hazard using regressors which characterise a linear spline in a variable equal to the number of months of eligible duration minus the number of elapsed UI spell months (including the current month). The range of the variable is thus from 0 (for those in the last month of UI eligibility) to 23. We use a linear spline in order to allow a non-monotonic association with the hazard (following Meyer, 1990, and Katz and Meyer, 1990).[16]

Coefficients on each spline variable show the change in the hazard associated with a one unit change in the number of months until exhaustion over the interval between the relevant knots. We use 6 knots, allowing effects to differ over 7 duration intervals, i.e. time-to-exhaustion = 0, 1, 2-3, 4-5, 6-11, 12-17, and 18-24 months.

Identification of the time-to-exhaustion effect is based on the variation in maximum entitlements across the sample separate from the variation in elapsed duration. This separate variation is greatest when time-to-exhaustion is imminent (values of time-to-exhaustion of 0, 1, and 2 are observed for all UI recipients) and declines with duration. Indeed values of time-to-exhaustion equal to 21, 22, and 23 are only observed for the group with 24 months potential duration; over this interval time-to-exhaustion is collinear with duration and hence not identified. Our formulation assumes that any potential time-to-exhaustion effect is the same for all values of 18 months or more.

Finally, ‘pure’ duration dependence in the re-employment hazard is captured non-parametrically, using separate indicator variables for each spell month.

We also explore whether there are variations in the effects of UI benefit levels with elapsed spell duration and age, estimating models of the form described by (7) and using appropriate definitions of z_{it} to incorporate the relevant interaction variables. Since the work of Nickell (1979a, b), there has been a well-established result from empirical studies of unemployment duration in Britain that unemployment benefit effects are insignificant for the long-term unemployed. (See also Narendranathan and Stewart 1993b.) The rationale is that the probability of receiving any job offer is likely to be very low and that any extra utility which might be gained from further unemployment is also low due to stigma or the general debilitation associated with long-term unemployment: ‘in this case, it is clear that the reservation wage will fall to a low level even to the extent that individual will follow the strategy of accepting the first job he is offered. Variations in the replacement ratio will then have no impact whatever on the probability of leaving unemployment and this is something we might expect to pick up for the long-term unemployed’ (Nickell, 1979. p.38).

Research has also pointed out that benefit effects may be greater for younger workers. Narendranathan, Nickell and Stern, for example, have argued for ‘the possibility that individuals facing fairly tight (low variance) wage distributions will exhibit larger benefit responses than those facing a much wider variation of potential wages. Younger workers are the natural group who face tight wage distributions ...’ (1989, p. 19).

4. RESULTS

[16] In preliminary analysis we also tried a quartic polynomial specification in time-to-exhaustion instead (cf. Ham and Rea, 1989), and it gave similar results for the shape of the time-to-exhaustion hazard and virtually identical results for the coefficients on the other covariates.

For a first look at the data, we present Kaplan-Meier estimates of empirical hazard functions for exits from UI to a job and for time-to-exhaustion. These can be interpreted as estimates of the monthly re-employment probability estimates not accounting for heterogeneity across UI recipients. Then we show estimates of the Kaplan-Meier cumulative failure rate function for various subgroups of the sample. Estimates of multivariate hazard regressions of the hazard and discussion of their implications follow.

4.1 Empirical hazard estimates

Figure 2 displays Kaplan-Meier estimates of the empirical hazard for exits from UI to a job derived from the pooled data from all 15 entry cohorts. In this graph, circles show the monthly exit hazard rates and the vertical lines through each circle span a 95% confidence interval for the hazard estimate. The estimates are all very precise because of the very large sample size.

A very clear pattern is revealed. The monthly re-employment hazard rises over the first three months of the UI spell and then declines. The rate of decline slows, however, as spells lengthen. Heterogeneity amongst UI recipients is a potential explanation for this shape. Imagine one group of recipients are ‘fast exiters’ with an increasing hazard and the remainder are ‘slow exiters’ with a declining hazard. The observed shape would then arise because of a sorting process. The rise in the hazard at short durations would be accounted for by the first group, but then increasingly the hazard for the second group would determine the shape of the overall hazard. One of the goals of the multivariate modelling is to see whether the shape of the hazard is the same once we have controlled for heterogeneity.

<Figure 2 near here>

There are small blips in the line traced out by the hazard line, for which UI exhaustion effects are one potential explanation. Observe that the hazard is slightly higher in each of months 2, 8, 11, 20 and 21 compared to the corresponding previous month, and these are months prior to exhaustion months (see Table 1). But before examining the time-to-exhaustion hazard explicitly, we shall examine the overall hazard in more detail.

For a look at potential seasonal and cyclical effects we have plotted the Kaplan-Meier estimates of the empirical hazard for exits from UI to a job separately for each of the fifteen UI entry cohorts. The Figures are shown in the Appendix Figure 2A.

It turns out that each graph is similar in shape to the one shown in Figure 1: each shows a rising hazard followed by a longer decrease. The greatest divergence in shape from the all-cohort hazard is for the entry cohorts of June and November 1991. In these cases the hazard remains more or less constant after the rise in the initial spell, rather than declining, but then declines much more sharply in the last 6 months. These latter spell months cover the beginning of 1993 when a recession hit the Spanish economy. (Note the sharp rise in unemployment rates and average steady-state duration in 1993 shown in Figure 1.) Other evidence of potential cyclical effects is revealed by the general shift down in hazards over the period, particularly in the first six months of a spell. For example the peaks in the hazard for 1987 are well above 0.06 for 1987 cohorts, but clearly below 0.6 for 1991 ones. A similar downward shift in the empirical hazard has been reported by Bover et al (1998, Figure 2) comparing 1989 and 1992. See also Narendranathan and Stewart (1995) who report lower hazards for Britain in a trough year (1987) compared to a peak year (1978).

There is also evidence of seasonal effects. Given the important role of agriculture and tourism in Spain, one would expect hazards to be higher in Spring and Summer as more labour was taken on for the season, and lower in Autumn and Winter when demand was lower. The graphs in the Appendix do indeed show some upward blips in the Spring spell months. (For the February entry cohorts, Spring corresponds to months 2, 3, 4 and 14, 15, 16; for the June cohorts, they are months 10, 11, 12 and 22, 23, 24; and for the November cohorts, months 5, 6, 7, and 17, 18, 19.)

4.2 Estimates of the cumulative proportion of UI recipients exiting to a job

Table 4 shows estimates of the cumulative proportion of UI recipients exiting to a job, with breakdowns for groups of UI recipients with different sets of characteristics. It is immediately obvious from the Table that unemployment durations in Spain are indeed rather long. Although one quarter of those beginning a UI spell had left to a job after 6 months, not even one half (48%) had left to a job after two years since entry.

<Table 4 near here>

There are noticeable differences between some groups of recipients however. Table 4 shows, for example, that the proportions remaining on UI after 6 months were much lower for the February and June 1991 entry cohorts—ones affected by the 1993 recession. (This tallies with the differences in empirical hazard functions discussed earlier.) Differences across cohorts in cumulative exit rates after two years are rather less marked however.

Older workers have very much smaller cumulative exit rates than younger workers do. After 6 months 30% of those aged less than 25 years on entry had left to job, whereas the corresponding proportion for those aged 52 or more was only 15%. After two years, the differential is the same: 60% compared to 29%.

There are also very marked differences in cumulative exit rates between workers who entered UI from a job with a fixed-term contract rather than a permanent contract. For example after two years, 59% of the former group had left UI to a job, but only 30% of the latter group. This is consistent with the differences by age (since younger workers are more likely to have jobs with fixed-term contracts), and the multivariate analysis is required to examine their separate effects.

There are intriguing differences by former job type. Those who had semi-skilled clerical or unskilled production jobs have noticeably higher cumulative exit rates. But those who had skilled clerical, technical or degree jobs have noticeably lower cumulative exit rates. Insider/outsider features of the market might explain this. Skilled clerical, technical or degree jobs may well be 'good jobs', but they are hard to regain once one has lost one.

Differences in cumulative exit rates between those resident in Andalucía or Extremadura compared to other regions, or between men with and without family responsibilities, are not very marked. Nor too are those between men with high and low replacement rates in the first six months of the UI spell—prima facie evidence that benefit effects may be small relative to other factors

4.3 Estimates of the time-to-exhaustion empirical hazard

Consider now the time-to-exhaustion empirical hazard shown in Figure 3. Values for months 21-23 are not shown given the problem of identification for this interval (see above). The hazard has a rather different shape to that shown for the USA: the US hazard is relatively flat between when there is between 4 and 52 weeks of UI entitlement remaining but then 'jumps dramatically the week before benefits end' (Meyer 1990, p. 766). In Spain the hazard is broadly U-shaped: decreasing with time when there is more than a year's entitlement remaining, relatively flat when there is between 6 and 12 months UI remaining, and then increasing as exhaustion approaches. But then it falls sharply in the last month before entitlement runs out. One potential explanation for the difference in US and Spanish hazard shapes just prior to exhaustion is that UA is more widely available in Spain, and anticipation of its receipt amongst those who are eligible reduces their UI exit hazards. The multivariate analysis, to which we now turn, enables us to investigate this hypothesis in more detail.

<Figure 3 near here>

4.4 Logistic hazard regression model estimates: (i) base case

Table 5 reports the ML estimates of two logistic hazard regression models of monthly re-employment probabilities. Model 1 does not include regional fixed effects amongst the regressors, whereas Model 2 does. The estimates of the fixed effects for Model 2, and the monthly duration dependence parameters (γ_t) for both models are shown in Appendix Table 5A. Virtually all parameter estimates are statistically significant at conventional levels, which is unsurprising given the sample size.

We favour Model 2 over Model 1 given the very large increase in log-likelihood (900, cf. $\chi^2(17, 0.01) = 33.4$). The only substantive difference between the two sets of coefficient estimates concerns that on the (log) regional unemployment rate. According to Model 1, re-employment probabilities are lower if job availability is lower, as expected. The estimated elasticity of the hazard with respect to the unemployment rate is about –0.08. However this association disappears entirely once regional fixed effects are included. The explanation was alluded to earlier: differentials in regional unemployment rates are very persistent over time, and so it is difficult to identify unemployment effects separately from regional effects. This story is supported by the pattern of coefficients on the regional fixed effects: for example monthly re-employment rates are about 90% lower in Andalucía and Extremadura (the regions with the highest unemployment rates) compared to those for Madrid, but about 25% higher in La Rioja (a low unemployment region). Differences in job availability are likely not the full explanation however. Recall that Andalucía and Extremadura also have a special UA scheme (which may have a disincentive effect). The importance of differences in regional unemployment rates has also been found in earlier Spanish studies (though they did not control for regional fixed effects).

We now turn to the estimates for other covariates, focusing attention on those from Model 2.

There are very large difference in re-employment probabilities associated with age. In particular, UI recipients aged 52+ at the start of the spell have hazards some 43% lower than recipients aged under 25 years ($-0.43 = e^{-0.556}-1$). On the other hand, hazard rates are broadly similar for all those aged 30-51 years. The sharp decline in the hazard for the over-50s is consistent with results reported by Ahn and Ugidos-Olazabal (1995), Alba Ramírez (1999), Bover et al (1996) and García Pérez (1997).

The hazard is some 10% higher for recipients who have family responsibilities relative to those who do not. Interpretation of this result is difficult given its non-specific definition. However, if one were to assume most persons with family responsibilities were married, then there is clearer story. Most earlier studies have found higher re-employment hazards for married men and attributed this to positive correlations between factors favouring marriage and employability, or to the greater pressure to get a job which greater needs might bring. A complementary explanation, of particular relevance to Spain, is that non-married persons receive transfers from other family members, which raises out-of-work utility.

The results for former job type exhibit patterns consistent with those reported in Table 4 about cumulative UI exit rates. Higher exit hazards are not associated with higher skill as one might expect. Relative to those who had unskilled production jobs, those who had semi-skilled or skilled production jobs, have hazards about 3% higher. However those from technical or degree jobs have hazards about 2% lower than unskilled production workers. Hazards are lower for former unskilled clerical workers (-10%) and very much lower for skilled clerical workers (by about 14%), and yet they are higher by about 12% for semi-skilled clerical workers. One explanation for these unexpected patterns may relate to the type of industry these people worked in. For example the skilled clerical category may cover retail/hotel and other service industries, for which studies based on the Spanish Labour Force

Survey (Encuesta de Población Activa, EPA) have shown lower hazards (Alba Ramírez, 1999; Bover et al, 1998).

The type of employment contract that the unemployed person had has a very strong association with exit rates from UI. Those who entered UI from a job with a fixed term or temporary contract have a re-employment hazard more than twice as large as the hazard for UI entrants from a job with a permanent contract. One obvious interpretation for this differential is that employers were more willing to take on workers on fixed-term contracts, and previous experience of such a contract provides a positive signal to an employer about willingness to accept such contracts. The size of the effect found here is likely to be over-estimate, however, and partly pick up the effects of variables not in the regressions. Other studies of exits from unemployment in Spain, with measures of marital status and educational attainments in their regressions, found smaller fixed-term contract effects than we have (Alba Ramírez, 1999, using the EPA; Ahn and Ugidos-Olazabal, 1995, and Alba-Ramírez and Freeman, 1990, using the 1985 Survey of Conditions of Life and Work (Encuesta de Conditiones de Vida y Trabajo, ECVT)).

There are clear seasonal patterns in the re-employment hazard. Compared to Winter's re-employment rates, those for Spring are about 25% higher, and those in Summer about 3% higher. By contrast hazards in Autumn are 5% lower than in Winter. This pattern is consistent with the seasonal hiring story given earlier, and with the results of Alba Ramírez (1999) and Bover et al (1998) using the EPA, who found that Quarter 2 re-employment rates were higher than Quarter 4 rates.

Re-employment rates are pro-cyclical. A one percentage point rise in the quarterly GDP growth rate is associated with a hazard some 8% higher. There are marked period effects in addition to those summarised by the GDP growth rate (as e.g. Bover et al. 1998 also found). Re-employment rates are higher in boom years and lower in recession years. Particularly marked are the low rates in 1993, when they are some 70% lower than rates in 1987, other things equal.

The elasticity of the re-employment hazard with respect to net earnings in the former job is 0.10. This figure is the same sign as found in other studies, but much smaller in absolute magnitude. For example, the elasticity in Meyer's (1990) US study, also based on adminstrative record data and net earnings from the former job, reports elasticities of at least 0.5. So too do Narendranathan and Nickell (1989) and Narendranathan and Stewart (1993a) using a prospective measure of the offered wage and British data. Put another way, despite measuring the offer wage in different ways the US and British studies found similar elasticities. This suggests that the smaller Spanish estimate may be due to differences in labour markets, i.e. the relative lack of responsiveness to the wage in Spain reflects the greater labour market rigidities in Spain relative to the US and Britain.

<Table 5 near here>

What about the responsiveness of the re-employment probability to changes in UI benefit levels? We find a relatively precisely determined elasticity of -0.16. This figure is of the expected sign but, again, is smaller than the estimates reported in the US and British studies cited in the last paragraph. And again it may be the relatively greater rigidities in the Spanish labour market which explain this. Using a standard Wald test, one can easily reject the 'replacement rate' hypothesis that log benefits and log former earnings have coefficients of equal magnitude and opposite signs.

Another potential explanation for the lower benefit elasticity in Spain may be to do with cross-national differences in UI coverage, and it may be that receipt per se is more relevant in the Spanish case. For example earlier Spanish studies based on the ECVT and EPA have reported strong negative associations between the re-employment hazard and receipt per se of unemployment benefits (Ahn and Ugidos-Olazabal, 1995; Ahn et al, 1998;

Alba Ramírez, 1998; Alba-Ramírez and Freeman, 1990; Bover et al, 1998; García Pérez, 1997), though these studies included no measures of the amount of UI received. Bover et al (1998) claimed that this omission may not be so crucial, citing earlier studies by Katz and Meyer (1990a) for example, as showing that 'benefit duration has significantly greater effects on unemployment duration than benefit levels (1996, p.3). We check this conjecture shortly.

We allowed for the possibility that benefit effects may differ for UI recipients resident in Andalucía and Extramadura. The coefficient on the interaction variable is indeed statistically significant at 0.18, implying a benefit elasticity little different from zero for this group—which is consistent with our prior hypothesis.

That UA benefit eligibility can have a substantive effect on re-employment probabilities is suggested by the statistically significant coefficient on the variable interacting age over 45 years and spell months after April 1989. We find that the extension of eligibility is associated with re-employment probabilities some 7% lower.

Time-to-exhaustion effects are summarised by the linear spline coefficient estimates in Table 5, summarised pictorially in Figure 4.[17]

<Figure 4 near here>

The shape of the hazard is broadly consistent with the predictions of the basic model in that it generally rises as exhaustion approaches, at least from 18 months duration onwards. However there are unexpected kinks very close to exhaustion, and in fact there is no statistically significant change in the time-to-exhaustion hazard in the very last month of eligibility. Overall the hazard function is relatively flat, especially when one takes account of the (pointwise) 95% confidence interval about the hazard. In sum it appears, contrary to Bover et al's (1998) conjecture, that time-to-exhaustion effects are not large in Spain, at least relative to the size of those found in North American studies (e.g. Ham and Rea, 1987, Canada; Meyer, 1990, USA) and for the Netherlands (Lindeboom and Theeuwes, 1993). Relatively small effects have also been found in other European countries (all with well-developed UA schemes): see Bratberg and Vaage (2000, Norway), Micklewright and Nagy (1996, Hungary) and Winter-Ebmer (1998, Austria).

The estimates of the 'pure' duration dependence, holding duration of benefit eligibility constant, are shown in Appendix Table 5A, and summarised pictorially in Figure 5. The hazard turns out to have a very similar shape to the empirical hazard shown in Figure 2 earlier, even with the multivariate controls for heterogeneity. One difference from the earlier picture is that the hazard peaks in the fourth month of the spell (rather than the third) before declining at a declining rate.

There remain some small blips in hazard at months just prior to or in potential exhaustion months (months 8, 12, 15, 20, 23), which suggests that there are some time-to-exhaustion effects (or heterogeneity effects like work experience associated with benefit eligibility) which are not fully captured by the time-to-exhaustion variable discussed in the previous paragraph. These blips are relatively small, however, and the principal impression derived from the results is the rise in the hazard followed by decline. Bover et al (1998, Figure 5) using a non-parametric baseline hazard report a rise in the hazard over the first three months of a spell followed by a decline in months 4-14. The main difference between our results is that their predicted hazard for UI recipients is flatter than ours after the initial peak (intriguingly it is their baseline hazard for non-recipients which has a more similar to

[17] This graph and the two following are drawn for a 'reference person' assumed to be aged 30 years with no family responsibilities, former job type was unskilled production, entered UI from a fixed-term contract job eligible for 24 months UI in total, regional unemployment rate = 18%, lives in Madrid, season and year fixed at winter 1987 values, and has mean values of log(real benefits), log (net earnings in former job), and quarterly GDP growth (see Table 3).

ours). García Pérez (1997) characterises duration dependence using a fifth-order polynomial in the logarithm of elapsed duration and finds similar results to Bover et al.

<Figure 5 near here>

The total hazard rate function, i.e. the variation in the hazard with elapsed duration while also taking into account time-to-exhaustion effects is shown in Figure 6. This is very similar in shape to the elapsed duration baseline hazard function (Figure 4), which confirms that time-to exhaustion effects, although statistically significant, appear to be relatively small in magnitude.

<Figure 6 near here>

4.5 Logistic hazard regression model estimates: (ii) interactions between benefits and duration

We now turn to consider whether the unemployment benefit disincentive effect reported in Models 1 and 2, which was constrained to be common to all recipients and invariant with elapsed duration, disguises important heterogeneity.

We first considered whether the benefit effect varied by spell month. In terms of the model specification summarised by (7), we included log(UI benefits) and log(earnings) in covariate vector z_{it} in addition to a constant term. The estimates of the month-specific benefit effects are shown in Table 6 in the 'Model 3' column. The remainder of the parameter estimates are shown in Appendix Table 6A. Inclusion of the interactions changed the coefficient estimates of other covariates very little: the models are robust.

<Table 6 near here>

The main finding is that benefit effects do indeed vary with duration, and in particular they are non-existent for the long-term unemployed, defined as those unemployed for 18 months or more. This is consistent with the British studies cited earlier (though 'long term unemployment' in that case referred to spells of 5-6 months or more). For spell months before the eighteenth, the benefit elasticity is typically larger than the constant elasticity estimated in Models 1 and 2, but nonetheless it is rather heterogeneous and not always statistically significant (spell months 1, 3, 6, 12, 16). It is even estimated to be positive in month 2.

Ours is the first study for Spain to investigate duration-specific benefit elasticities. The most closely related research is by Bover et al. (1998) who included in their model an interaction term between log(duration) and the receipt of unemployment benefits. (Recall that they had no measure of benefit levels in their data.) They found that the reduction in the re-employment hazard associated with benefit receipt decreased with duration, 'closing up after one year of unemployment' (1998, p. 26).

We re-estimated Model 3 constraining the benefit elasticity to be fixed during three month intervals: see the Model 4 estimates in Table 6. This was in part a reaction to the findings of statistically insignificant interaction effects, and thence an attempt to find a compromise model in-between assuming a constant elasticity and assuming some duration-specific variation. As it happens a likelihood ratio test favours Model 3 rather than Model 4 (test statistic χ^2(40, d.f. = 16), p-value < 0.0001). However this may be a reflection of the large sample size and, in any case, the constrained model does reveal the same patterns as the month-specific model, including the statistically insignificant benefit elasticities for the long-term unemployed. Since we wanted to subsequently investigate heterogeneity in benefit effects by e.g. age, and this could only be done by reducing the number of interaction covariates used (or else the models became too large to estimate), we work further with this specification.

We investigated heterogeneity in benefit elasticities by age as well as elapsed duration, by extending Model 4 to allow for age-group-specific elasticities for each of the 8 duration intervals: see Table 7. For each of the three age groups distinguished (20-29, 30-51, 52+ years), benefit elasticities are insignificantly zero for the long-term unemployed. Otherwise, for each age group, the elasticities fluctuate over the spell.

Effects appear slightly greater for those aged 20-29 compared to those aged 30-51. Although the null hypothesis that the quarterly effects were the same for the two groups can be rejected using a likelihood ratio test (χ^2(254, d.f. = 16), p-value < 0.0001), this may be a reflection of the large sample size. What is most striking about the results is that the disincentive effects, where they exist, are largest in magnitude for men aged 52-59. This is also contrary to what one might expect (see earlier), and the patterns across age groups certainly contrast with those found for Britain. Narendranathan et al. (1989) and Narendranathan and Stewart (1995), for example, found a greater benefit effect for men aged under 20 than for prime-age men (aged 20-44) with still smaller or no effect for men aged 45-64. Using data for 1987, Narendranathan and Stewart (1993b) found weekly benefit effects only for teenagers. That there are cross-country differences may not be surprising, but the nature of the Spanish patterns is puzzling nonetheless.

<Table 7 near here>

We also investigated whether monthly UI benefit effects differed for persons with relatively high replacement rates (over 0.90) compared to those with lower replacement rates, but found no statistically significant differences.

5. CONCLUDING COMMENTS

We have provided new evidence for Spain about the determinants of re-employment probabilities and hence unemployment duration, using a rich new data set for a very large sample of UI recipients. One of our main goals has been to ascertain the impact of the unemployment benefit system, stressing that this may be manifested in several dimensions. We have found some statistically significant impacts but they are relatively small in magnitude. Specifically, there are disincentive effects from higher benefit levels but these evaporate for the long-term unemployed. Time-to-exhaustion effects are small. There is some 'pure' duration dependence in the baseline hazard rate, but this follows a clear rise in the hazard in the first three to four months of a spell. The importance of considering UA benefits for incentives, not only UI benefits, is underlined by the association between lower re-employment rates and the extension of UA eligibility for those aged 45 years or more in 1989. The much lower re-employment rates for those aged 52+ may reasonably also be interpreted as an UA effect.

Noticeably larger effects on the re-employment hazard appear to be associated with institutional features of the Spanish economy, and changes in the demand for labour, rather than with unemployment benefits. There are very big differentials in hazard rates according to whether one entered UI from a job with a fixed-term or permanent contract. This underscores the remarks of others about the insider/outsider nature of the Spanish labour market, with the attendant rigidities. The relevance of labour demand effects is underscored by the large seasonal and cyclical effects and regional differences.

In sum, our results provide further support for the conclusions of Blanchard et al. (1995, p. 5) about what was required for a successful reduction of unemployment in Spain, namely a sustained expansion in demand, combined with reforms to the structure of collective bargaining and restrictions on lay-offs within the context of a social pact. At the margin these measures are likely to be more promising than further modifications to the unemployment benefit system. Our results suggesting relatively small benefit system effects are based on the behaviour of entrants to UI before the reductions in UI generosity introduced in 1992, and so subsequent effects may well be smaller still.

REFERENCES

Ahn, N. and Ugidos-Olazabal, A. (1995). 'Duration of unemployment in Spain: relative effects of unemployment benefit and family characteristics', *Oxford Bulletin of Economics and Statistics*, 57, 249-264.

Ahn, N., de la Rica, S., and Ugidos, A. (1998). 'Employment and unemployment duration in the Spanish youth labour market', unpublished paper, Universidad del País Vasco, Bilbao.

Alba Ramírez, A. (1998). 'How temporary is temporary employment in Spain?', *Journal of Labor Research*, 19, 695-710.

Alba Ramírez, A. (1999). 'Explaining the transitions out of unemployment in Spain: the effect of unemployment insurance', *Applied Economics*, 31, 183-193.

Alba-Ramírez, A. and Freeman, R. (1990). 'Jobfinding and wages when longrun unemployment is really long: the case of Spain', Working Paper No. 3409, National Bureau of Economic Research, Cambridge MA.

Allison, P.D. (1982). 'Discrete-time methods for the analysis of event histories', in *Sociological Methodology 1982*, S. Leinhardt (ed.), Jossey-Bass Publishers, San Francisco, 61-97.

Andrés, J., García, J., and Jiménez, S. (1989). 'La incidencia y la duración del desempleo masculino en España', *Moneda y Crédito*, 188, 75-124.

Atkinson, A.B. and Micklewright, J. (1991), 'Unemployment compensation and labor market transitions: a critical review', *Journal of Economic Literature*, 29, 1679-1727.

Atkinson, A.B., Gomulka, J., Micklewright, J. and Rau, N. (1984), 'Unemployment benefit, duration and incentives in Britain: how robust is the evidence?', *Journal of Public Economics*, 23, 3-26.

Bentolila, S. and Dolado, J.J. (1994). 'Spanish labour markets', *Economic Policy*, 18, 53-99.

Blanchard, O., Jimeno, J.F., Andrés, J., Bean, C., Malinvaud, E., Revenga, A., Saint-Paul, G., Snower, D.J., Solow, R., Taguas, D., Toharia, L. (1995). *Spanish Unemployment: Is There a Solution?*, Centre for Economic Policy Research, London.

Blanco, J.M. (1992). 'Los efectos del seguro de desempleo sobre la actividad laboral y las horas trabajadas', *Moneda y Crédito*, 195, 283-258.

Bover, O., Arellano, M., and Bentolila, S. (1998). 'Unemployment duration, benefit duration, and the business cycle', Discussion Paper 1840, Centre for Economic Policy Research, London.

Bratberg, E. and Vaage, K. (2000) 'Spell durations with long unemployment insurance periods', *Labour Economics*, 7, 152-180.

Cebrián, I., García, C., Muro, J., Toharia, L., and Villagómez, E. (1996). 'The influence of unemployment benefits on unemployment duration: evidence from Spain', *Labour*, 10, 239-267.

Dolado, J.J. and Jimeno, J.F. (1997). 'The causes of Spanish unemployment: a structural VAR approach', *European Economic Review*, 41, 1281-1307.

Dolton, P. and van der Klaauw, W. (1995). 'Leaving teaching in the UK: a duration analysis', *Economic Journal*, 105, 431-444.

García-Pérez, J.I. (1997). 'Las tasas de salida del empleo y el desempleo en España (1978-1993)', *Investigaciones Económicas*, 21, 29-53.

García-Pérez, J.I. (1998). 'Non-stationary job search with firing: a structural estimation', unpublished paper, CEMFI, Madrid.
García-Serrano, C. (1997). 'Spanish unemployment and benefits', in: Paul Gregg (ed.) *Jobs, Wages and Poverty: Patterns of Persistence and Mobility in the New Flexible Labour Market*, Centre for Economic Performance, London School of Economics, London.
Ham, J. and Rea, S.A. Jr. (1987). 'Unemployment insurance and male unemployment duration in Canada', *Journal of Labor Economics*, 5, 325-353.
Jenkins, S.P. (1995). 'Easy estimation methods for discrete-time duration models', *Oxford Bulletin of Economics and Statistics*, 57, 129-138.
Jenkins, S.P. (1997). 'sbe17. Discrete time proportional hazards regression (pgmhaz)', *Stata Technical Bulletin*, 39, 22-32.
Jimeno, J.F. and Bentolila, S. (1998). 'Regional unemployment persistence (Spain, 1976-1994)', *Labour Economics,* 5, 25-52.
Katz, L.F. and Meyer, B.D. (1990a). 'The impact of the potential duration of unemployment benefits on the duration of unemployment', *Journal of Public Economics*, 41, 45-72.
Katz, L.F. and Meyer, B.D. (1990b). 'Unemployment insurance, recall expectations, and unemployment outcomes, *Quarterly Journal of Economics*, 105, 973-1002.
Lancaster, T. (1979). 'Econometric methods for the duration of unemployment', *Econometrica*, 47, 939-956.
Lancaster, T. (1990). *The Econometric Analysis of Transition Data*, Econometric Society Monograph No. 17, Cambridge University Press, Cambridge.
Layard, R., Nickell, S, and Jackman, R. (1991). *Unemployment: Macroeconomic Performance and the Labour Market*, Oxford University Press, Oxford.
Lindenboom, M. and Theeuwes, J. (1993). 'Search, benefits and entitlement', *Economica*, 60, 327-346.
Meyer, B.D. (1990). 'Unemployment insurance and unemployment spells', *Econometrica*, 58, 757-782.
Micklewright, J., and Nagy, Gy. (1996). 'Labour market policy and the unemployed in Hungary', *European Economic Review*, 40, 819-828.
Moffitt, R. (1985) 'Unemployment insurance and the distribution of unemployment spells', *Journal of Econometrics*, 28, 85-101.
Mortensen, D.T., (1977). 'Unemployment insurance and job search decisions', *Industrial and Labor Relations Review*, 30, 505-517.
Narendranathan, W. and Nickell, S. (1989). 'Modelling the process of job search', in: S. Nickell, W. Narendranathan, J. Stern, and J. Garcia, *The Nature of Unemployment in Britain: Studies of the DHSS Cohort*, Oxford University Press, Oxford, 47-77. (First published in *Journal of Econometrics*, 28 (1985), 155-169.)
Narendranathan, W., Nickell, S., and Stern, J. (1989). 'Unemployment benefits revisited', in: S. Nickell, W. Narendranathan, J. Stern, and J. Garcia, *The Nature of Unemployment in Britain: Studies of the DHSS Cohort*, Oxford University Press, Oxford, 11-46. (First published in *Economic Journal* 95 (1985), 307-329.)
Narendranathan, W. and Stewart, M. (1993a). 'Modelling the probability of leaving unemployment: competing risks models with flexible base-line hazards', *Applied Statistics*, 42, 63-83.
Narendranathan, W. and Stewart, M. (1993b). 'How does the benefit effect vary as unemployment spells lengthen?', *Journal of Applied Econometrics*, 8, 361-381.
Narendranathan, W. and Stewart, M. (1995). 'The determinants of individual unemployment durations in an era of high unemployment', *Economic Journal*, 105, 321-332.
Nickell, S. (1979a). 'Estimating the probability of leaving unemployment', *Econometrica*, 47, 1249-66.

Nickell, S. (1979b). ‘The effect of unemployment and related benefits on the duration of unemployment’, *Economic Journal*, 89, 34-49.

OECD (1991). ‘Unemployment benefit rules and labour market policy’, *Employment Outlook, July 1991*, OECD, Paris.

Prentice, R. and Gloeckler, L. (1978). ‘Regression analysis of grouped survival data with application to breast cancer data’, *Biometrics*, 34, 57-67.

Robinson, A. (1997). ‘Spanish family values’, *New Economy*, 4, 188-192.

Toharia, L. (1997). *Spain*, Labour Market Studies Series No. 1, Employment and Social Affairs, European Commission, Brussels.

Winter-Ebmer, R. (1998) ‘Potential unemployment benefit duration and spell length: lessons from a quasi-experiment in Austria’, *Oxford Bulletin of Economics and Statistics*, 60, 33-45.

Figure 1. Trends in unemployment for Spanish men, 1977-1996

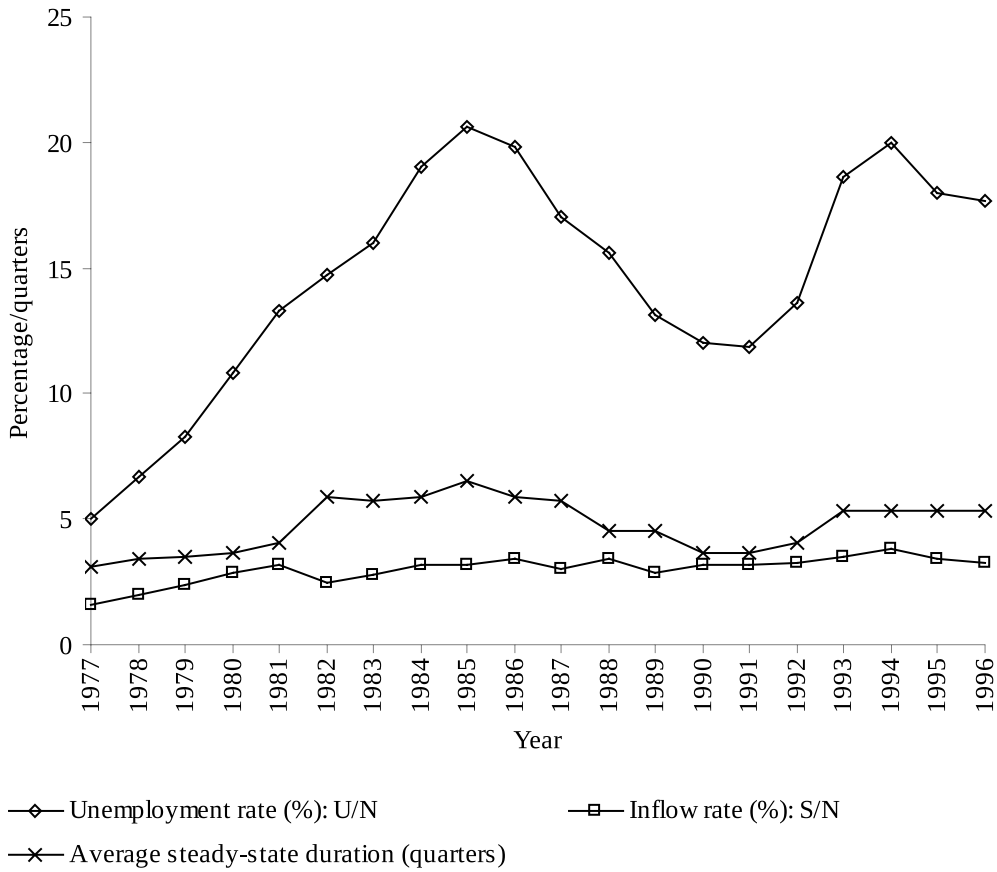
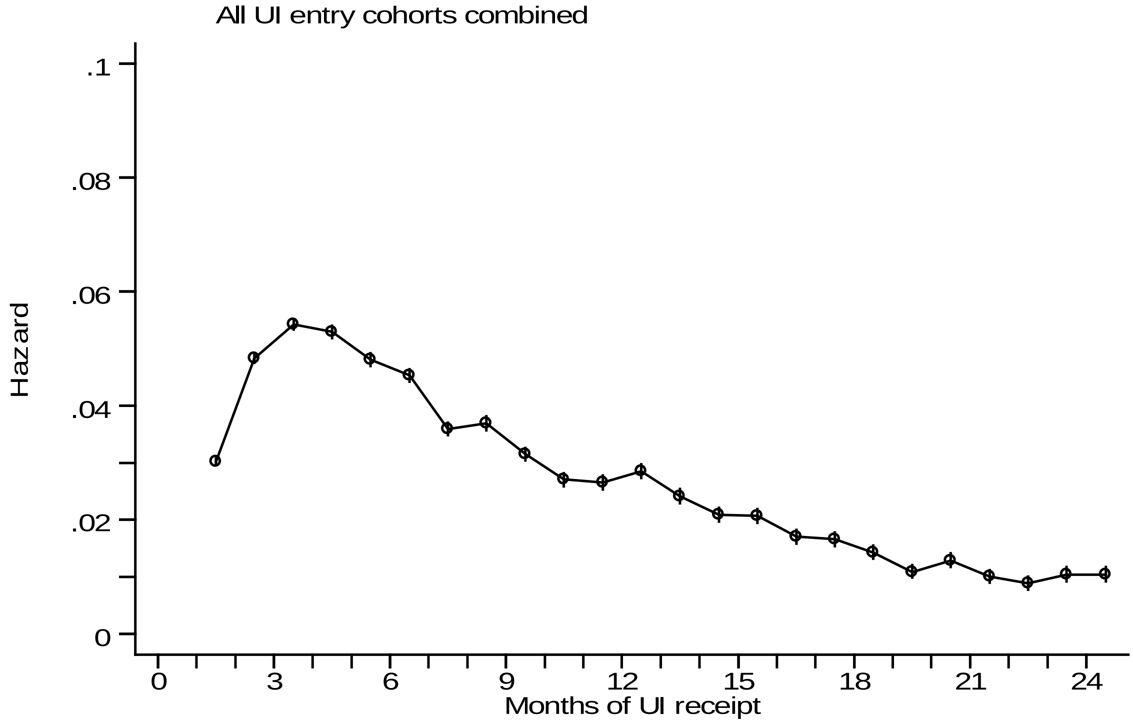


Figure 2. Kaplan-Meier empirical hazard function for exits from UI to a job:



Note: vertical lines through points show 95% confidence interval for monthly hazard.

Table 1. The UI entitlement period in Spain depends on UI contributions made in previous jobs

Contribution period over the previous 48 months (months)	UI entitlement (months)
6-12	3
12-18	6
18-24	9
24-30	12
30-36	15
36-42	18
42-48	21
48-	24

Pre-1992 system. See text for further details of the system and subsequent changes to the rules.

Table 2.
Types of exit from UI by Spanish men aged 20-59, by UI entry cohort (row percentages)

Cohort		Exhaust - no UA	Exhaust to UA	Exit to job	Exit – other	All (column %)
1987	February	26.5	29.9	30.1	13.6	(4.8)
	June	28.5	28.3	28.3	15.0	(4.3)
	November	40.5	28.4	23.3	7.8	(8.9)
1988	February	26.5	27.8	31.8	13.9	(5.2)
	June	28.4	26.3	30.6	14.7	(4.8)
	November	37.0	25.6	27.2	10.2	(7.8)
1989	February	28.6	27.2	30.6	13.7	(5.5)
	June	30.3	26.3	28.3	15.1	(5.3)
	November	39.3	26.8	24.7	9.3	(8.7)
1990	February	28.2	26.8	30.9	14.2	(5.7)
	June	31.4	26.8	28.6	13.3	(5.9)
	November	37.6	27.4	25.1	9.9	(9.2)
1991	February	28.1	26.4	28.6	16.9	(6.8)
	June	28.7	26.2	24.6	20.5	(7.1)
	November	28.8	25.9	20.4	25.0	(10.2)
All cohorts combined		32.1	27.0	26.8	14.2	100

Source: authors' calculations from SIPRE files. Total number of cases = 329,947. Reasons for 'other' exits from UI include: death, retirement, permanent disability, emigration, and self-employment start-ups subsidised with UI.

Table 3. Variables and summary statistics: Spanish male UI recipients aged 20-59.

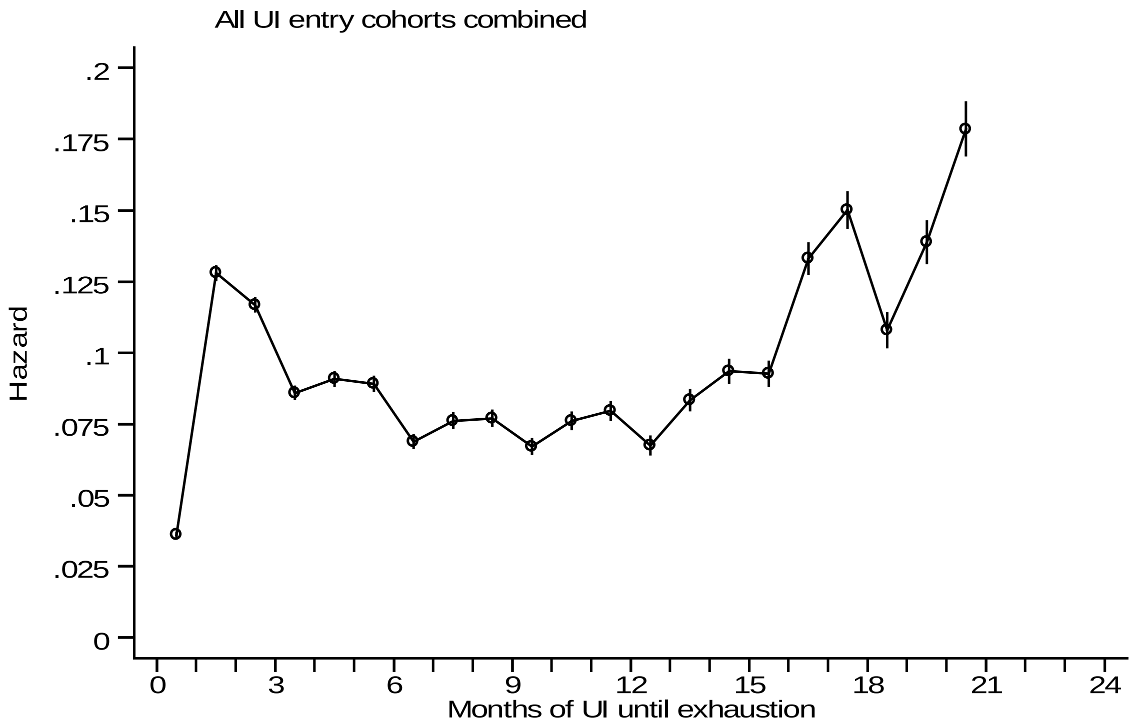
	mean	std.dev.	min	max
Months of UI receipt	7.3	6.6	1	24
Months of UI receipt entitlement at spell start	9.6	7.7	3	24
Age at start of UI spell (years)	33.4	10.5	20	59
Age 20-24	0.23		0	1
Age 25-29	0.23		0	1
Age 30-34	0.16		0	1
Age 35-39	0.11		0	1
Age 40-44	0.09		0	1
Age 45-51	0.09		0	1
Age 52+	0.09		0	1
Has family responsibilities	0.27		0	1
Former job type:				
degree, technical	6.1		0	1
assistant technician or skilled clerical	7.5		0	1
semi-skilled clerical	3.2		0	1
unskilled clerical	4.8		0	1
skilled production	31.9		0	1
semi-skilled production	18.0		0	1
unskilled production	28.6		0	1
Entered UI from a job with a fixed-term contract	0.82		0	1
Gross replacement rate, months 1-6 of spell	0.78	0.10	0.06	1.15
Gross replacement rate, months 7-12 of spell	0.67	0.15	0.06	1.15
Gross replacement rate, months 13+ of spell	0.65	0.16	0.04	1.15
Net replacement rate, months 1-6 of spell	0.92	0.09	0.12	1.22
Net replacement rate, months 7-12 of spell	0.79	0.14	0.12	1.22
Net replacement rate, months 13+ of spell	0.75	0.14	0.07	1.22
Net earnings in former job (Pesetas per month, after tax, Feb 87 prices)	74032	25128	33746	653434
UI benefit (Pesetas per month, Feb 87 prices) [a]	62715	16019	41310	108520
log(net earnings in former job)	11.2	0.29	10.4	13.4
log(UI benefit) [a]	11.0	0.24	10.6	11.6
Quarterly regional unemployment rate (%) [a]	17.4	5.8	7.3	34.2
Quarterly GDP growth rate (%) [a, b]	0.81	0.45	-0.55	1.6

Number of spells = 329,947; 2,397,685 spell months at risk of exit from UI to a job. [a] : time-varying covariate (statistics derived from person-month file). All variables derived directly from SIPRE data, except [b]: quarterly regional unemployment rates (source: Labour Force Survey, EPA), quarterly GDP growth rates (National Accounts), and tax liabilities on earnings to give net rather than gross earnings (authors' estimates).

Table 4. Cumulative proportion of UI recipients who left UI to a job after 6, 12, 18, and 24 months (Kaplan-Meier estimates), by subgroup

	Months since UI entry			
	6	12	18	24
All	0.25	0.38	0.45	0.48
UI entry cohort				
February 1987	0.27	0.37	0.44	0.48
June 1987	0.25	0.36	0.42	0.47
November 1987	0.27	0.40	0.47	0.51
February 1988	0.28	0.39	0.46	0.50
June 1988	0.27	0.39	0.45	0.49
November 1988	0.29	0.41	0.46	0.50
February 1989	0.28	0.39	0.45	0.48
June 1989	0.25	0.36	0.42	0.46
November 1989	0.26	0.39	0.46	0.49
February 1990	0.27	0.39	0.45	0.48
June 1990	0.24	0.36	0.43	0.46
November 1990	0.24	0.38	0.45	0.48
February 1991	0.23	0.36	0.45	0.48
June 1991	0.20	0.36	0.45	0.47
November 1991	0.20	0.40	0.45	0.46
Age at UI entry				
Less than 25 years	0.30	0.47	0.56	0.60
25-29	0.27	0.41	0.49	0.53
30-34	0.24	0.38	0.45	0.49
35-39	0.24	0.36	0.42	0.45
40-44	0.24	0.36	0.43	0.46
45-51	0.23	0.35	0.42	0.47
52+	0.15	0.22	0.27	0.29
Lives in Andalucía or Extremadura	0.22	0.35	0.42	0.46
Lives outside Andalucía and Extremadura	0.26	0.39	0.45	0.49
Has family responsibilities	0.25	0.37	0.43	0.47
Without family responsibilities	0.25	0.38	0.45	0.48
Entered UI from job with fixed-term contract	0.28	0.45	0.54	0.59
Entered UI from job with permanent contract	0.14	0.22	0.27	0.30
Former job type:				
Degree, technical	0.22	0.32	0.37	0.41
Assistant technician or skilled clerical	0.19	0.28	0.34	0.38
Semi-skilled clerical	0.27	0.42	0.49	0.53
Unskilled clerical	0.23	0.37	0.45	0.49
Skilled production	0.25	0.38	0.45	0.48
Semi-skilled production	0.26	0.39	0.46	0.49
Unskilled production	0.26	0.42	0.51	0.55
Net replacement rate, months 1-6 of spell, > 90%	0.25	0.38	0.45	0.49
Net replacement rate, months 1-6 of spell, $\leq$ 90%	0.25	0.37	0.43	0.46

Figure 3. Kaplan-Meier empirical hazard function for time-to-UI-exhaustion



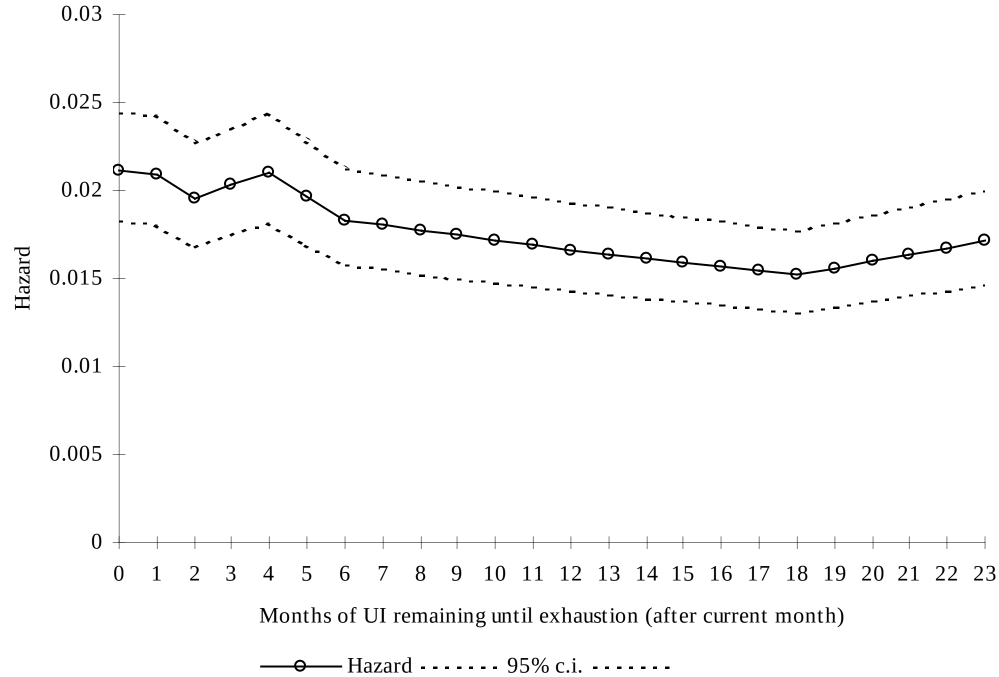
Note: vertical lines through points show 95% confidence interval for monthly hazard.

Table 5. Logistic hazard regression models of re-employment probability

	Model 1		Model 2	
	coeff.	(s.e.)	coeff.	(s.e.)
Aged 25-29	-0.064	(0.010)	-0.058	(0.010)
Aged 30-34	-0.137	(0.012)	-0.132	(0.012)
Aged 35-39	-0.181	(0.014)	-0.174	(0.014)
Aged 40-44	-0.148	(0.015)	-0.141	(0.015)
Aged 45-51	-0.122	(0.019)	-0.112	(0.019)
Aged 52-59	-0.561	(0.021)	-0.556	(0.021)
Has family responsibilities	0.082	(0.008)	0.099	(0.009)
Entered UI from a job with a fixed-term contract	0.756	(0.011)	0.763	(0.011)
Log(regional unemployment rate)	-0.079	(0.020)	0.007	(0.042)
Former job: degree, technical	-0.038	(0.017)	-0.024	(0.018)
Former job: assistant technician or skilled clerical	-0.162	(0.015)	-0.159	(0.015)
Former job: semi-skilled clerical	0.120	(0.020)	0.109	(0.020)
Former job: unskilled clerical	-0.071	(0.017)	-0.072	(0.017)
Former job: skilled production	0.050	(0.009)	0.062	(0.009)
Former job: semi-skilled production	0.035	(0.011)	0.024	(0.011)
Log(real UI benefit) [a]	-0.093	(0.041)	-0.157	(0.042)
Lives in South * log(real UI benefit) [a, b]	-0.021	(0.001)	0.184	(0.041)
Log(real earnings in former job)	0.141	(0.035)	0.098	(0.035)
Aged 45-64 * (spell month after April 1989) [a]	-0.068	(0.020)	-0.065	(0.020)
Spring quarter [a]	0.226	(0.010)	0.223	(0.010)
Summer quarter [a]	0.029	(0.010)	0.032	(0.010)
Autumn quarter [a]	-0.053	(0.012)	-0.048	(0.012)
Year is 1988 [a]	0.096	(0.017)	0.104	(0.017)
Year is 1989 [a]	0.055	(0.016)	0.077	(0.017)
Year is 1990 [a]	-0.002	(0.026)	0.027	(0.027)
Year is 1991 [a]	-0.122	(0.031)	-0.090	(0.032)
Year is 1992 [a]	0.022	(0.045)	0.047	(0.045)
Year is 1993 [a]	-1.189	(0.124)	-1.189	(0.124)
Quarterly GDP growth rate (%)[a]	0.076	(0.028)	0.078	(0.028)
Linear spline in time-to-exhaustion				
month 0	-0.010	(0.018)	-0.011	(0.018)
month 1	-0.067	(0.018)	-0.069	(0.018)
months 2-3	0.039	(0.009)	0.037	(0.009)
months 4-5	-0.070	(0.009)	-0.071	(0.009)
months 6-11	-0.016	(0.003)	-0.016	(0.003)
months 12-17	-0.014	(0.004)	-0.015	(0.004)
Months 18+	0.024	(0.006)	0.024	(0.006)
Regional fixed effects	No		Yes	
Log-likelihood	-363533		-362626	

Number of spells = 329,947 (2,397,685 spell-months). [a]: time-varying covariate. Reference categories: aged < 25 years, lives in Madrid region, no family responsibilities, former job type was unskilled production, had a permanent contract, spell month in Winter 1987. 'South' refers to Andalucía and Extremadura. Monthly duration dependence parameters and regional fixed effects shown in Appendix Table 5A.

Figure 4. Time-to-exhaustion hazard rate (Model 2 estimates)



Graphs refer to man aged 30 with no family responsibilities, living in Madrid, former job type was unskilled production with a fixed-term contract, regional unemployment rate = 18%, GDP growth rate = 0.81%, spell month in Winter 1987. Log(former earnings) and log(UI benefits) set at sample mean values. Entered UI eligible for 24 months UI in total.

Figure 5. Baseline hazard rate (Model 2 estimates, UI eligibility = 24 months)

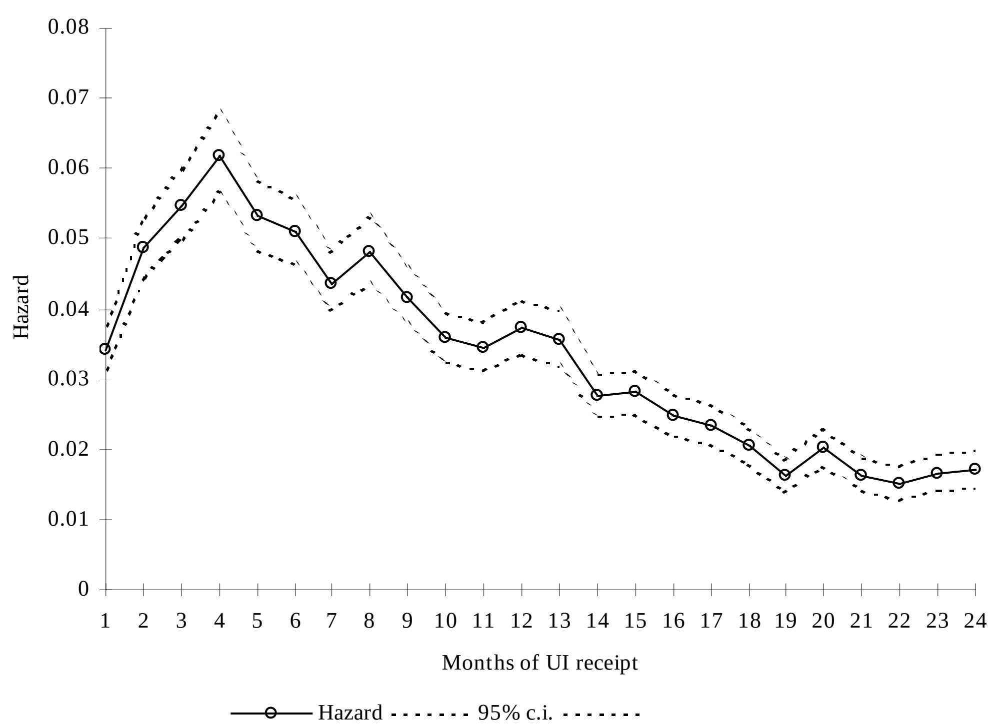
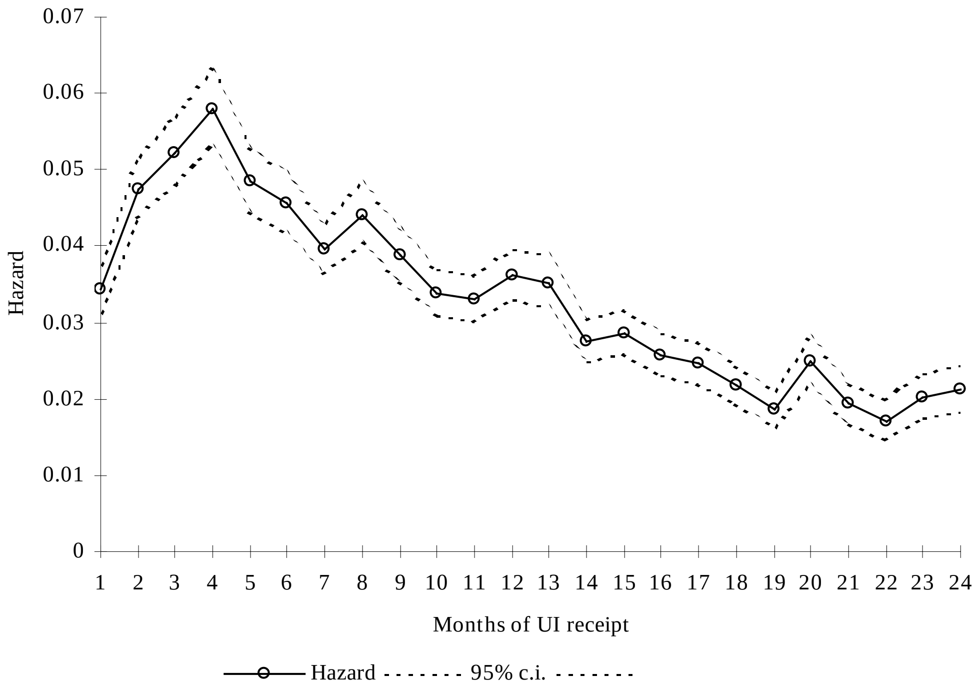


Figure 6. Total hazard rate (Model 2 estimates)



Graph refers to man aged 30 with no family responsibilities, living in Madrid, former job type was unskilled production with a fixed-term contract, regional unemployment rate = 18%, GDP growth rate = 0.81%, spell month in Winter 1987. Log(former earnings) and log(UI benefits) set at sample mean values. Entered UI eligible for 24 months UI in total.

Table 6. Logistic hazard regression models of re-employment probability, with the UI benefit effect varying with elapsed duration

	Model 3			Model 4	
Spell month	Coeff	(s.e.)	Spell months	coeff	(s.e.)
1	0.157	(0.118)			
2	0.449	(0.101)	1-3	0.183	(0.061)
3	-0.032	(0.096)			
4	-0.409	(0.123)			
5	-0.507	(0.134)	4-6	-0.328	(0.078)
6	-0.015	(0.144)			
7	-0.809	(0.203)			
8	-0.733	(0.204)	7-9	-0.790	(0.122)
9	-0.839	(0.226)			
10	-0.736	(0.266)			
11	-0.683	(0.271)	10-12	-0.594	(0.156)
12	-0.361	(0.270)			
13	-0.841	(0.329)			
14	-0.603	(0.355)	13-15	-0.765	(0.201)
15	-0.851	(0.364)			
16	-0.417	(0.428)			
17	-0.928	(0.445)	16-18	-0.524	(0.258)
18	-0.197	(0.473)			
19	-0.204	(0.630)			
20	0.267	(0.575)	19-21	0.164	(0.357)
21	0.405	(0.656)			
22	0.203	(0.780)			
23	-0.682	(0.735)	22-24	0.001	(0.432)
24	0.459	(0.728)			
Log likelihood	-362446			-362486	

Table shows estimates of duration-specific coefficients on log(real UI benefits). Model also includes covariates used in Model 2 (Table 5), plus interactions between duration and log(earnings): estimates are shown in Table 6A. Number of spells = 329,947 (2,397,685 spell-months).

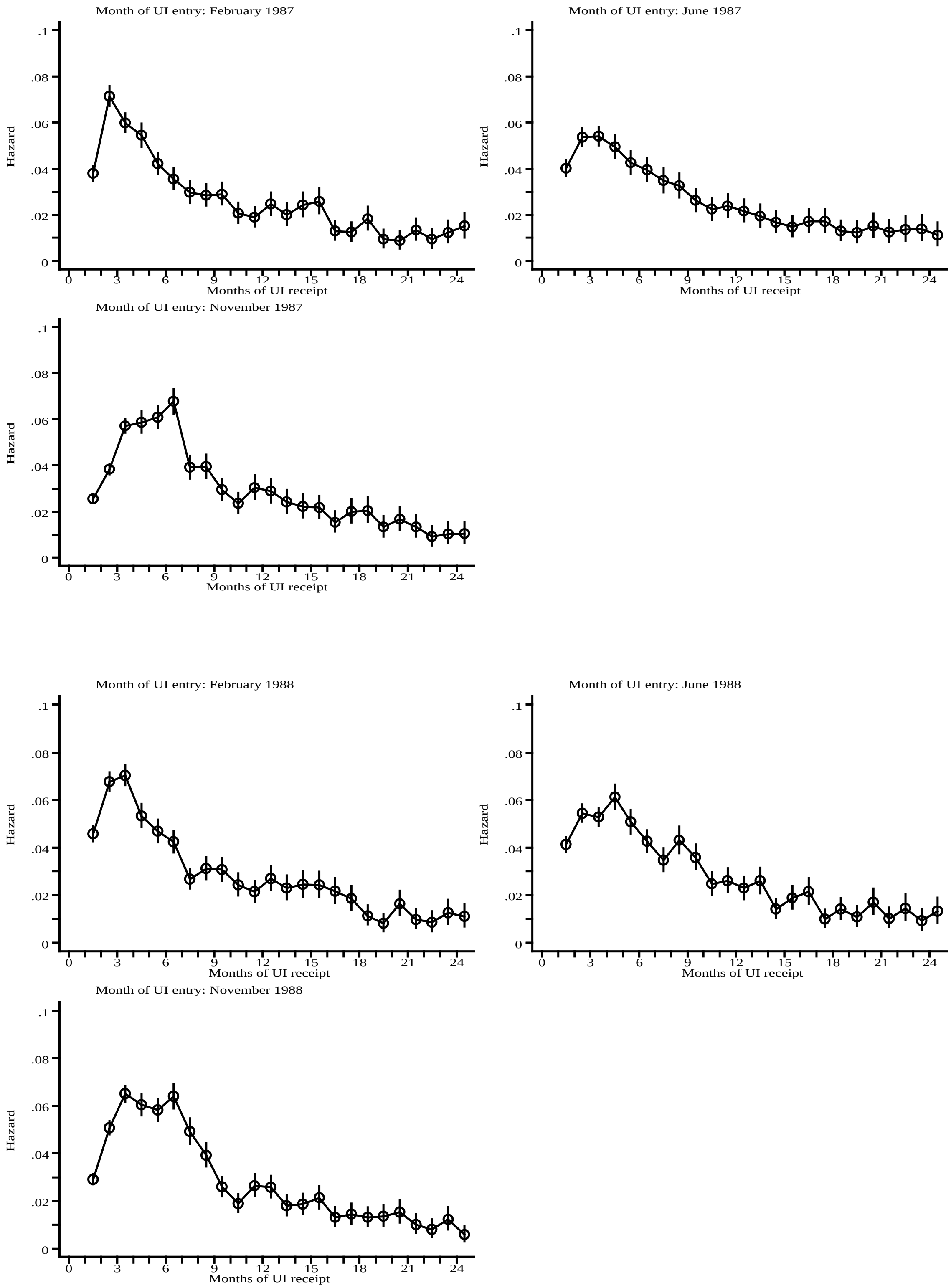
Table 7. Logistic hazard regression model of re-employment probability, with the UI benefit effect varying with elapsed duration and age group

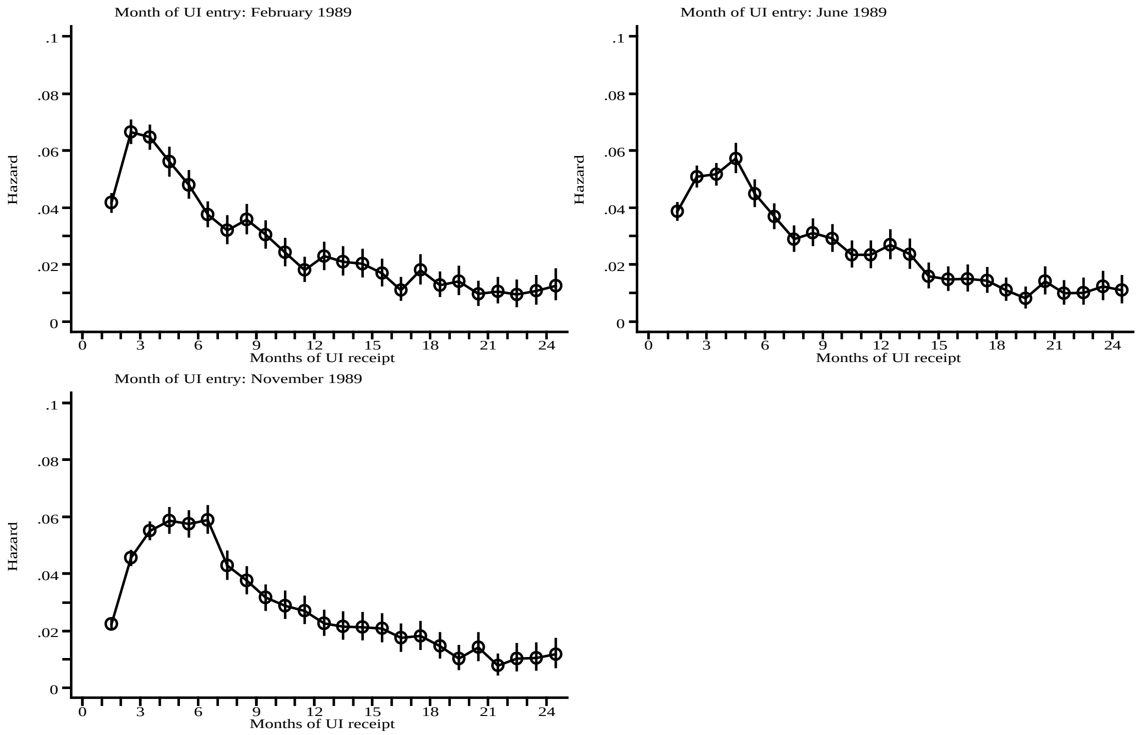
Model 5								
Aged 20-29			Aged 30-51			Aged 52-59		
Spell months	coeff	(s.e.)	Spell months	coeff	(s.e.)	Spell months	coeff	(s.e.)
1-3	0.242	(0.087)	1-3	0.078	(0.082)	1-3	0.437	(0.235)
4-6	-0.481	(0.112)	4-6	-0.316	(0.100)	4-6	0.404	(0.273)
7-9	-0.813	(0.171)	7-9	-0.734	(0.157)	7-9	-1.198	(0.369)
10-12	-0.775	(0.224)	10-12	-0.412	(0.198)	10-12	-0.661	(0.437)
13-15	-0.635	(0.257)	13-15	-0.561	(0.259)	13-15	-1.864	(0.514)
16-18	-0.856	(0.359)	16-18	0.027	(0.317)	16-18	-1.557	(0.634)
19-21	0.029	(0.583)	19-21	0.455	(0.420)	19-21	-0.814	(0.776)
22-24	0.011	(0.839)	22-24	0.032	(0.504)	22-24	-0.543	(0.837)
Log likelihood = -362324								

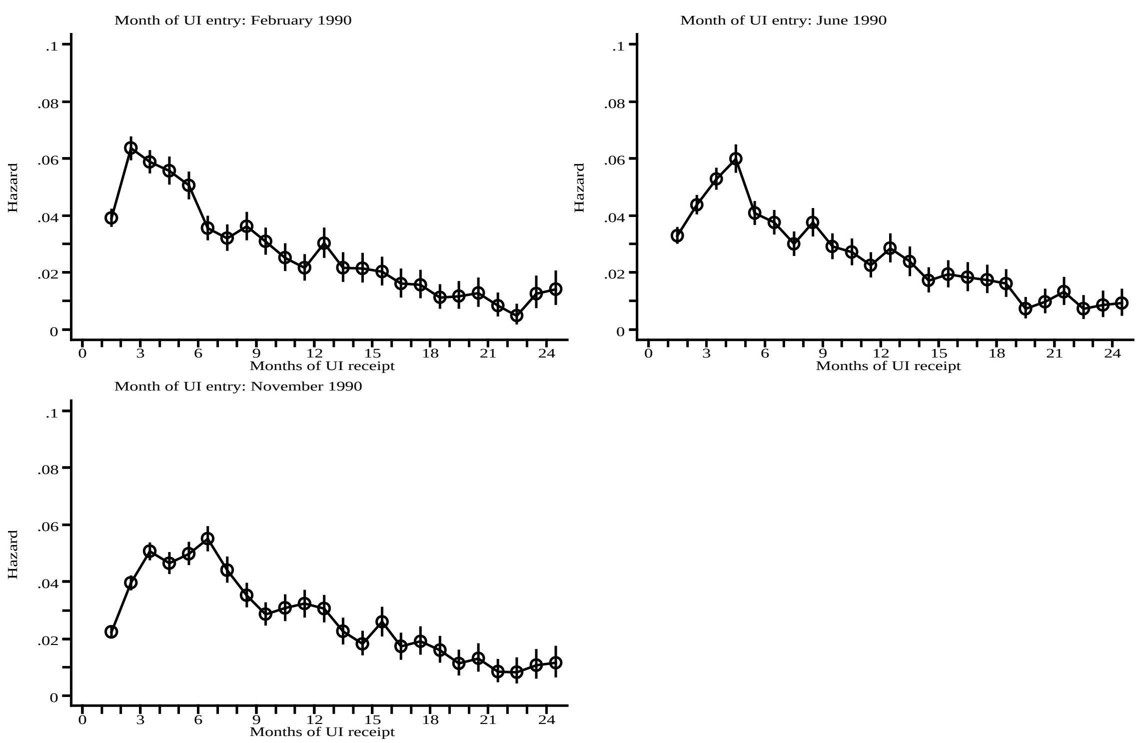
Table shows estimates of duration-specific coefficients on log(real UI benefits) separately for each age group. Model also includes covariates used in Model 2 (Table 5), plus interactions between duration, age group, and log(earnings): estimates are shown in Table 7A. Number of spells = 329,947 (2,397,685 spell-months).

APPENDIX

Figure 2A. Kaplan-Meier empirical hazard function for exits from UI to a job, by cohort of entry to UI




Month of UI entry: February 1989
Month of UI entry: June 1989
Month of UI entry: November 1989
Hazard
.1
.08
.06
.04
.02
0
0 3 6 9 12 15 18 21 24
Months of UI receipt


Month of UI entry: February 1990
Month of UI entry: June 1990
Month of UI entry: November 1990
Hazard
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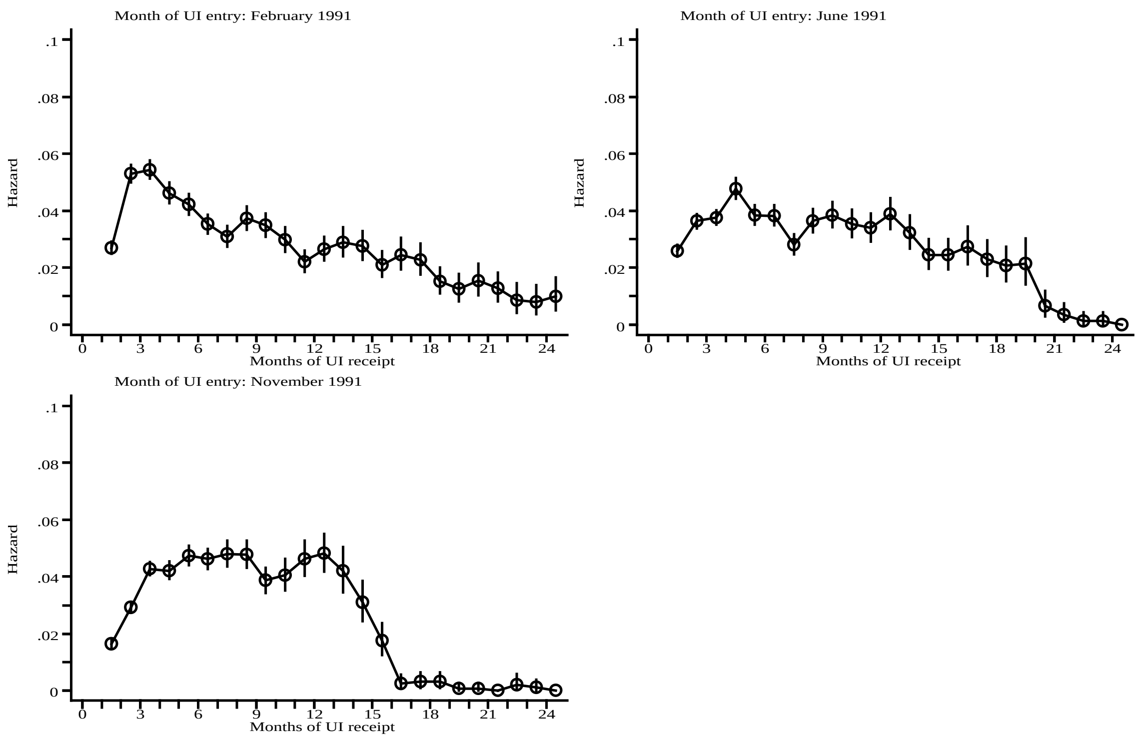
Months of UI receipt


Month of UI entry: February 1991
Hazard
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Months of UI receipt
Month of UI entry: June 1991
Hazard
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0 3 6 9 12 15 18 21 24
Months of UI receipt
Month of UI entry: November 1991
Hazard
.1
.08
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0
0 3 6 9 12 15 18 21 24
Months of UI receipt

Table 5A. Table 5 continued (Logistic hazard regression models of re-employment probability for men)

	Model 1		Model 2	
	coeff.	(s.e.)	Coeff.	(s.e.)
Spell month (γ_t)				
1	-4.226	(0.212)	-3.150	(0.253)
2	-3.865	(0.211)	-2.786	(0.252)
3	-3.741	(0.211)	-2.663	(0.252)
4	-3.608	(0.212)	-2.531	(0.253)
5	-3.768	(0.212)	-2.692	(0.253)
6	-3.814	(0.211)	-2.737	(0.252)
7	-3.974	(0.209)	-2.897	(0.251)
8	-3.869	(0.210)	-2.797	(0.252)
9	-4.019	(0.210)	-2.947	(0.251)
10	-4.178	(0.210)	-3.104	(0.252)
11	-4.216	(0.210)	-3.141	(0.251)
12	-4.136	(0.210)	-3.064	(0.252)
13	-4.174	(0.210)	-3.108	(0.251)
14	-4.445	(0.209)	-3.377	(0.250)
15	-4.422	(0.209)	-3.355	(0.251)
16	-4.546	(0.211)	-3.481	(0.252)
17	-4.601	(0.211)	-3.540	(0.252)
18	-4.746	(0.211)	-3.684	(0.252)
19	-4.980	(0.213)	-3.920	(0.254)
20	-4.748	(0.214)	-3.693	(0.254)
21	-4.962	(0.214)	-3.909	(0.255)
22	-5.049	(0.218)	-3.998	(0.258)
23	-4.942	(0.217)	-3.891	(0.256)
24	-4.907	(0.216)	-3.860	(0.256)
Region (Madrid = ref.)				
Andalucía			-2.506	(0.457)
Aragón			-0.233	(0.025)
Asturias			-0.444	(0.022)
Baleares			-0.071	(0.026)
Canarias			-0.352	(0.034)
Cantabria			-0.246	(0.015)
Castilla-La Mancha			0.015	(0.020)
Castilla-León			-0.041	(0.020)
Cataluña			-0.293	(0.018)
Comunidad Valenciana			-0.318	(0.021)
Extremadura			-2.002	(0.459)
Galicia			-0.122	(0.014)
Murcia			-0.053	(0.033)
Navarra			-0.250	(0.021)
País Vasco			0.194	(0.027)
La Rioja			0.223	(0.045)

Table shows the estimates of the duration dependence parameters and regional fixed effects for models shown in Table 5.

Table 6A. Table 6 continued (Logistic hazard regression models of re-employment probability, with the UI benefit effect varying with elapsed duration)

	Model 3		Model 4	
	coeff	(s.e.)	coeff	(s.e.)
Aged 25-29	-0.064	(0.010)	-0.064	(0.010)
Aged 30-34	-0.137	(0.012)	-0.137	(0.012)
Aged 35-39	-0.176	(0.014)	-0.176	(0.014)
Aged 40-44	-0.140	(0.015)	-0.140	(0.015)
Aged 45-51	-0.115	(0.019)	-0.115	(0.019)
Aged 52-59	-0.554	(0.021)	-0.553	(0.021)
Has family responsibilities	0.101	(0.009)	0.101	(0.009)
Entered UI from a job with a fixed-term contract	0.752	(0.011)	0.752	(0.011)
Log(regional unemployment rate)	0.019	(0.042)	0.021	(0.042)
Former job: degree, technical	-0.022	(0.018)	-0.021	(0.018)
Former job: assistant technician or skilled clerical	-0.156	(0.015)	-0.156	(0.015)
Former job: semi-skilled clerical	0.105	(0.020)	0.105	(0.020)
Former job: unskilled clerical	-0.075	(0.017)	-0.075	(0.017)
Former job: skilled production	0.057	(0.009)	0.057	(0.009)
Former job: semi-skilled production	0.020	(0.011)	0.020	(0.011)
Aged 45-64 * (spell month after April 1989) [a]	-0.059	(0.020)	-0.059	(0.020)
Linear spline in time-to-exhaustion				
month 0	-0.017	(0.018)	-0.013	(0.018)
month 1	-0.065	(0.018)	-0.072	(0.018)
months 2-3	0.037	(0.009)	0.039	(0.009)
months 4-5	-0.071	(0.009)	-0.071	(0.009)
months 6-11	-0.015	(0.003)	-0.015	(0.003)
months 12-17	-0.015	(0.004)	-0.015	(0.004)
months 18+	0.011	(0.006)	0.012	(0.006)
Spring quarter [a]	0.225	(0.010)	0.226	(0.010)
Summer quarter [a]	0.032	(0.010)	0.033	(0.010)
Autumn quarter [a]	-0.050	(0.012)	-0.048	(0.012)
Year is 1988 [a]	0.100	(0.017)	0.101	(0.017)
Year is 1989 [a]	0.071	(0.017)	0.073	(0.017)
Year is 1990 [a]	0.022	(0.027)	0.023	(0.027)
Year is 1991 [a]	-0.099	(0.032)	-0.098	(0.032)
Year is 1992 [a]	0.039	(0.045)	0.041	(0.045)
Year is 1993 [a]	-1.175	(0.124)	-1.173	(0.124)
Quarterly GDP growth rate (%) [a]	0.075	(0.028)	0.076	(0.028)
Region (Madrid = ref.)				
Andalucía	-2.163	(0.455)	-2.160	(0.455)
Aragón	-0.224	(0.025)	-0.224	(0.025)
Asturias	-0.442	(0.022)	-0.442	(0.022)
Baleares	-0.073	(0.026)	-0.073	(0.026)
Cantabria	-0.358	(0.034)	-0.359	(0.034)
Canarias	0.015	(0.020)	0.014	(0.020)
Castilla-La Mancha	-0.248	(0.015)	-0.248	(0.015)
Castilla-León	-0.042	(0.020)	-0.042	(0.020)

Cataluña	-0.290	(0.018)		-0.291	(0.018)
Comunidad Valenciana	-0.321	(0.021)		-0.321	(0.021)
Extremadura	-1.656	(0.457)		-1.654	(0.457)
Galicia	-0.120	(0.014)		-0.119	(0.014)
Murcia	-0.057	(0.033)		-0.057	(0.033)
Navarra	-0.259	(0.021)		-0.259	(0.021)
País Vasco	0.187	(0.027)		0.186	(0.027)
La Rioja	0.224	(0.045)		0.224	(0.045)
Spell month (γ_t)					
1	-7.912	(0.565)		-6.058	(0.325)
2	-4.745	(0.477)		-5.695	(0.324)
3	-5.277	(0.463)		-5.572	(0.324)
4	-2.279	(0.587)		-2.105	(0.391)
5	-1.471	(0.636)		-2.270	(0.391)
6	-2.943	(0.664)		-2.317	(0.390)
7	0.748	(0.874)		0.216	(0.540)
8	-0.746	(0.869)		0.314	(0.540)
9	0.846	(0.965)		0.161	(0.539)
10	0.290	(1.122)		-0.044	(0.670)
11	-0.935	(1.141)		-0.083	(0.669)
12	0.505	(1.131)		-0.007	(0.669)
13	2.581	(1.509)		1.906	(0.930)
14	-0.558	(1.588)		1.633	(0.929)
15	3.211	(1.688)		1.653	(0.929)
16	2.706	(1.954)		1.840	(1.166)
17	2.400	(1.968)		1.779	(1.166)
18	-0.072	(2.096)		1.632	(1.165)
19	1.262	(2.573)		1.427	(1.490)
20	3.775	(2.473)		1.650	(1.489)
21	-0.935	(2.667)		1.431	(1.488)
22	2.508	(3.200)		-1.891	(1.687)
23	-2.053	(2.813)		-1.787	(1.686)
24	-4.975	(2.787)		-1.760	(1.685)
Lives in South * log(real UI benefit)	0.152	(0.041)		0.151	(0.041)
*Log(real earnings in former job)*spell month*					
Month 1	0.214	(0.099)			
2	-0.328	(0.087)	1-3	0.021	(0.051)
3	0.208	(0.081)			
4	0.324	(0.101)			
5	0.335	(0.110)	4-6	0.228	(0.064)
6	-0.025	(0.120)			
7	0.411	(0.165)			
8	0.480	(0.165)	7-9	0.440	(0.099)
9	0.427	(0.183)			
10	0.361	(0.215)			
11	0.416	(0.218)	10-12	0.252	(0.126)
12	-0.023	(0.219)			
13	0.254	(0.246)			
14	0.280	(0.268)	13-15	0.240	(0.151)
15	0.184	(0.271)			

16	-0.204	(0.321)			
17	0.317	(0.337)	16-18	-0.023	(0.195)
18	-0.189	(0.358)			
19	-0.322	(0.493)			
20	-0.987	(0.444)	19-21	-0.696	(0.278)
21	-0.719	(0.515)			
22	-0.837	(0.613)			
23	0.443	(0.586)	22-24	-0.246	(0.344)
24	-0.405	(0.582)			

Notes as for Table 5 in main text.

Table 7A. Table 7 continued (Logistic hazard regression model of re-employment probability, with the UI benefit effect varying with elapsed duration and age group)

	Model 5	
	coeff	(s.e.)
Aged 25-29	-0.077	(0.010)
Aged 30-34	0.581	(0.391)
Aged 35-39	0.542	(0.391)
Aged 40-44	0.576	(0.391)
Aged 45-51	0.594	(0.391)
Aged 52-59	8.425	(0.748)
Has family responsibilities	0.101	(0.009)
Entered UI from a job with a fixed-term contract	0.736	(0.011)
Log(regional unemployment rate)	0.012	(0.042)
Former job: degree, technical	-0.022	(0.018)
Former job: assistant technician or skilled clerical	-0.157	(0.015)
Former job: semi-skilled clerical	0.102	(0.020)
Former job: unskilled clerical	-0.077	(0.017)
Former job: skilled production	0.057	(0.009)
Former job: semi-skilled production	0.020	(0.011)
Aged 45-64 * (spell month after April 1989) [a]	-0.048	(0.020)
Linear spline in time-to-exhaustion		
month 0	-0.013	(0.018)
month 1	-0.071	(0.018)
months 2-3	0.039	(0.009)
months 4-5	-0.071	(0.009)
months 6-11	-0.015	(0.003)
months 12-17	-0.015	(0.004)
months 18+	0.012	(0.006)
Spring quarter [a]	0.225	(0.010)
Summer quarter [a]	0.032	(0.010)
Autumn quarter [a]	-0.049	(0.012)
Year is 1988 [a]	0.103	(0.017)
Year is 1989 [a]	0.073	(0.017)
Year is 1990 [a]	0.023	(0.027)
Year is 1991 [a]	-0.099	(0.032)
Year is 1992 [a]	0.038	(0.045)
Year is 1993 [a]	-1.175	(0.124)
Quarterly GDP growth rate (%)[a]	0.079	(0.028)
Region (Madrid = ref.)		
Andalucía	-2.047	(0.456)
Aragón	-0.225	(0.025)
Asturias	-0.440	(0.022)
Baleares	-0.073	(0.026)
Cantabria	-0.350	(0.034)
Canarias	0.017	(0.020)
Castilla-La Mancha	-0.249	(0.015)
Castilla-León	-0.045	(0.020)
Cataluña	-0.290	(0.018)
Comunidad Valenciana	-0.315	(0.021)

Extremadura	-1.539	(0.458)
Galicia	-0.122	(0.014)
Murcia	-0.058	(0.033)
Navarra	-0.261	(0.021)
País Vasco	0.187	(0.027)
La Rioja	0.220	(0.045)
Spell month (γ_t)		
1	-6.836	(0.390)
2	-6.473	(0.390)
3	-6.349	(0.390)
4	-3.165	(0.456)
5	-3.328	(0.456)
6	-3.375	(0.455)
7	-0.820	(0.603)
8	-0.722	(0.604)
9	-0.873	(0.603)
10	-1.718	(0.732)
11	-1.755	(0.732)
12	-1.678	(0.732)
13	-0.150	(0.995)
14	-0.421	(0.994)
15	-0.400	(0.994)
16	-0.310	(1.230)
17	-0.370	(1.230)
18	-0.515	(1.229)
19	-0.397	(1.558)
20	-0.173	(1.556)
21	-0.391	(1.556)
22	-3.141	(1.757)
23	-3.038	(1.757)
24	-3.011	(1.755)
Lives in South * log(real UI benefit)	0.142	(0.041)
*Log(real earnings in former job)*spell month* duration*		
Age <30; months 1-3	0.035	(0.075)
Age <30; months 4-6	0.480	(0.099)
Age <30; months 7-9	0.558	(0.151)
Age <30; months 10-12	0.588	(0.200)
Age <30; months 13-15	0.310	(0.219)
Age <30; months 16-18	0.505	(0.316)
Age <30; months 19-21	-0.393	(0.533)
Age <30; months 22-24	-0.150	(0.788)
Age 30-51; months 1-3	0.134	(0.073)
Age 30-51; months 4-6	0.249	(0.088)
Age 30-51; months 7-9	0.417	(0.137)
Age 30-51; months 10-12	0.159	(0.173)
Age 30-51; months 13-15	0.158	(0.215)
Age 30-51; months 16-18	-0.432	(0.260)
Age 30-51; months 19-21	-0.879	(0.348)
Age 30-51; months 22-24	-0.225	(0.423)

Age 52-59; months 1-3	-0.962	(0.219)
Age 52-59; months 4-6	-1.203	(0.256)
Age 52-59; months 7-9	0.128	(0.344)
Age 52-59; months 10-12	-0.340	(0.411)
Age 52-59; months 13-15	0.699	(0.474)
Age 52-59; months 16-18	0.374	(0.587)
Age 52-59; months 19-21	-0.377	(0.719)
Age 52-59; months 22-24	-0.397	(0.771)

Notes as for Table 5 in main text.