Unemployment Duration, Benefit Duration, and the Business Cycle

Olympia Bover
Banco de España

Manuel Arellano
CEMFI

Samuel Bentolila
CEMFI

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E-mail addresses: bover@bde.es, arellano@cemfi.es, bentolila@cemfi.es.
CEMFI, Casado del Alisal 5, 28014 Madrid, Spain.
Tel: 341 4290551, fax: 341 4291056, http://www.cemfi.es.

Abstract

In this paper we study the effects of unemployment benefit duration and the business cycle on unemployment duration. We construct durations for individuals entering unemployment from a longitudinal sample of Spanish men in 1987-1994. Estimated discrete hazard models indicate that receipt of unemployment benefits significantly reduces the hazard of leaving unemployment. For instance, at durations of 3 months, the hazard for workers without benefits is twice as large as that for workers with benefits. Favorable business conditions increase the hazard of leaving unemployment. At sample-period magnitudes, this effect is significantly smaller than that of benefit receipt.

Abstract

JEL *classification*: J64, J65, E32.

Key words: unemployment duration, unemployment benefits, business cycle.

1 Introduction

Do unemployment benefits lead to longer unemployment spells? In principle we expect so, since individuals would be more selective concerning job offers the larger their out-of-work income. Moreover, standard search theory predicts that, under certain conditions, increases in either the amount or the length of unemployment benefits should lengthen the duration of unemployment. Nevertheless, the effects of benefits on unemployment duration compound supply and demand characteristics of the labor market, so that their magnitude is an empirical issue.

In this paper we investigate the effect of receiving unemployment benefits on unemployment duration in Spain, using a newly released longitudinal Labor Force Survey (LFS). These data have certain features which are well suited for our purpose. First of all, by matching its successive waves, we are able to construct a database of unemployment spells covering the period 1987-1994. Secondly, in this dataset individuals provide information on their labor market status for up to six consecutive quarters. Some retrospective information is also provided, but the large sample size of the LFS, together with the extended period of observation, allows us to concentrate on individuals entering unemployment around the time of interview, whose information we expect to be more reliable. In this way, we also avoid having to rely on corrections for stock sample bias, while still having a sample of entrants in which 46% of the durations are completed before the individual exits from the sample. A third crucial aspect of our dataset is that the sample period spans a full business cycle of the Spanish economy, enabling us to take into account changes in aggregate conditions. As a drawback, we observe whether an individual is receiving unemployment benefits or not as long as he remains unemployed, but we lack information on the actual level of benefits. Moreover, the length of benefit entitlement is a censored variable, since it is only observed if benefits are exhausted before the end of the unemployment spell and the individual still remains in the sample at that time.

Thus, our basic empirical comparison is between the exit rates of those with and without benefits at given durations, holding constant demographic, sectoral, and aggregate variables. We believe this is a meaningful exercise, given the allocation of benefits in the labor market we study. In our sample, 50% of the spells correspond to workers without benefits from the outset. The distribution of demographic and occupational characteristics is fairly evenly spread between the two groups, although younger workers are more likely to have no benefits. Whether a given worker has benefits or not depends essentially on the length of his previous job. In the mid 1980's, a labor market reform introduced new fixed-term labor contracts, with much lower firing costs than the traditional permanent contracts. This caused a swift increase in the proportion of temporary employees, and also an increase in labor turnover rates. As a consequence, those who started a job after the reform were more likely to do so under a temporary labor contract, and also more likely to have no right to benefits in the event of losing the job. These contracts were not restricted to specific types of workers, but were widely used, and they now comprise around one third of all employees. As a result, we do not expect endogenous self-selection of workers into the no benefit category to be a dominant feature of the relationship between exit rates and benefits. However, if the absence of benefits were associated with particular characteristics that made workers less employable, we would expect this to cause a downward bias in the measured effect of benefits on exit rates.

The existing empirical evidence from US and UK microeconomic data shows relatively small estimates of the effects of benefit amounts on average unemployment duration.[1] With regard to benefit length, the more telling evidence is the presence of spikes in the exit rate from unemployment around the time of benefit exhaustion (see, e.g., Katz and Meyer (1990), for the US).[2] While having a sample of entrants over the business cycle helps us overcome some of the problems often encountered in cross-sectional duration analysis (*i.e.* stock sampling and short time spans), the focus of our research is different to these studies and so the results are not readily comparable. Firstly, time aggregation in our spells –which are measured in months– means that our data are uninformative on exit rates at very short durations. However, since the late 1970's, Spain has had the worst unemployment record in the OECD, with the unemployment rate rising over our sample period from 16% to a staggering 24% of the labor force. These high rates have come along with extremely long durations: in 1994, 56% of the unemployed had been such for more than a year. This feature makes the analysis of monthly exit rates over the business cycle a more meaningful exercise than it would be if durations were shorter. Secondly, given that we do not have any information on the levels of benefits or family income, we cannot estimate their effects on exit rates. Nevertheless, recent empirical evidence suggests that the latter omission may not be so crucial. More specifically, both Gritz and MaCurdy (1989) and Katz and Meyer (1990) find that benefit duration has

[1] Typical estimates for the US imply that a 10% increase in the amount of benefits would lengthen average duration by 1 to 1.5 weeks (Moffit and Nicholson (1982) and Meyer (1990), respectively). For the UK the increase is estimated between 0.5 and 1 week (Narendranathan *et al.* (1985) and Lancaster and Nickell (1980), respectively). See Atkinson and Micklewright (1991) for a survey.

[2] For Spain, a number of studies using cross-section data from a 1985 Ministry of Finance survey have found positive effects of imputed benefit eligibility (actual receipt being unobserved) on duration: Alba-Ramirez and Freeman (1990), Ahn and Ugidos (1995), and Blanco (1995), while Andrés and García (1993) only find an effect when sectoral dummies are excluded. Also, Cebrián *et al.* (1995) find a spike in the exit rate in the last 3 months of benefit receipt –with data on recipients in 1987-92–, though it is only steep for workers with entitlements up to 9 months. The latter three studies find small effects of the replacement ratio on the hazard of leaving unemployment.

significantly greater impact on unemployment duration than benefit levels. For example, according to the latter, a given expenditure cut achieved by reducing benefit duration would have twice the effect on unemployment duration as one achieved by cutting benefit levels.[3] Thirdly, while our data allows us to measure the effect of receiving benefits on exit rates, we cannot calculate the impact of a given benefit duration on average unemployment duration, without making very restrictive assumptions. This is due to observing the presence of benefits while unemployed, but not the entitlement length. We can make robust comparisons of exit rates for workers with and without benefits, but we cannot reconstruct the distribution of durations for a given entitlement without making untestable assumptions. Lastly, a major objective of this paper is to study the effects of business cycle conditions on exit rates and to compare them with benefit effects, something we can afford owing to the nature of our dataset.[4]

Concerning econometric methods, we estimate logistic discrete hazard models by maximum likelihood. Using discrete models, as opposed to continuous-time models is a natural choice in our context, given that we observe monthly durations. We specify both duration dependence and calendar time effects in a flexible way. Moreover, we treat benefits as a predetermined but not strictly exogenous variable in the hazard model. This is motivated by the fact that knowledge about benefit receipt at future durations can be expected to have an effect on current exit rates. We also consider an extended version of the model allowing for unobserved heterogeneity that is correlated with benefits. In doing so, we discuss the implications of introducing unobserved

[3] Also, Layard *et al.* (1991) find that benefit duration is much more important than the replacement ratio (the ratio of benefits to the previous wage) in explaining aggregate unemployment persistence in OECD countries.

[4] A few papers, like Meyer (1990) or Imbens and Lynch (1994), also provide estimates of business cycle effects.

heterogeneity in discrete duration models with predetermined variables. We proceed by specifying a reduced form process for benefits and by maximizing a joint mixture likelihood for the unemployment and benefit durations. The estimates of the model with unobserved heterogeneity do not alter our main empirical conclusions in any significant way.

The paper is structured as follows. In section 2 we briefly present the predictions of standard search theory about the effects of unemployment benefits. In section 3 we describe both the relevant features of Spanish labor market institutions and our database. In section 4 we discuss the empirical models and econometric techniques, and in section 5 we present the empirical results. Section 6 contains the conclusions.

2 Theoretical framework

2.1 Unemployment duration and benefits

Economic theory predicts that, under certain conditions, both higher levels and longer periods of unemployment benefits lower the hazard of leaving unemployment, and therefore result in higher unemployment duration.

The standard framework for analyzing this issue is well known, as contained for example in Mortensen (1977). The representative worker is assumed to maximize the present value of his lifetime utility, which depends on income and leisure. Income when employed is equal to the wage, and to benefits when unemployed. Benefits are received as long as the worker has been laid off from a job and has not reached the maximum benefit duration (which depends on past employment history). There is a stationary distribution of wage offers (jobs) and workers' search activity is represented as random draws from that distribution. The probability of leaving unemployment is the product of the probability of receiving an offer times the probability of accepting it. It is affected, among other things, by the worker's decision variables: search intensity and the reservation wage. On the one hand, the probability of receiving an offer is proportional to the intensity of search. On the other hand, the worker's optimal decision rule is to accept any wage offer above a certain reservation wage level.

Three key results concerning benefits emerge in this setup. First, as exhaustion of benefits draws nearer search intensity rises and the reservation wage falls, so that the hazard increases. Second, when benefits are exhausted, the hazard rate jumps to a higher level (as long as income and leisure are strict complements in utility), remaining constant thereafter. Third, an increase in the amount or the maximum duration of unemployment benefits raises the opportunity cost of search, thereby leading to a reduction in the hazard. This *disincentive effect* of benefits may be countered by an *entitlement effect:* an increase in benefits increases the expected utility from future, as opposed to current, unemployment spells with benefits. Thus, for a currently unemployed worker without benefits, an increase in the benefit level or duration raises the exit rate from unemployment (*i.e.*, employment becomes more valuable because it gives right to now-enhanced future benefits). Since future events are discounted for both uncertainty and time preference reasons, we expect this to be a second-order effect for workers with benefits.

Later work has relaxed some of the assumptions in the standard model described above, leading to qualifications of the predictions regarding benefits (see Atkinson and Micklewright (1991)). For example, receipt of unemployment benefits may permit an increase in the resources devoted to search by liquidity constrained individuals, thereby leading to increased hazards. Therefore the prediction of a disincentive effect of benefits may be partially or totally offset for certain individuals or periods by entitlement or other effects, and assessing this becomes an empirical question.

2.2 Duration, the business cycle, and hysteresis

Search theory does not provide an unambiguous prediction on the sign of the relationship between the business cycle and unemployment duration. Higher growth raises the probability of receiving a job offer, but it also tends to increase reservation wages.[5] Empirical work has not resolved the issue either. For example, with US data, Meyer (1990) finds that a higher state unemployment rate raises the hazard rates of unemployment benefit claimants, while Imbens and Lynch (1994) find that a higher local unemployment rate lowers the hazard rates of young unemployed workers.[6] The latter paper is one of the few that uses a long period sample. Thus, firmer conclusions may be reached as more work is done on longer samples, like the one exploited in this paper.

Business cycle effects on individual unemployment duration are typically captured in empirical work by variables like GDP growth or the unemployment rate (in levels and/or rates of change). Recent research has pointed out a new channel through which the change in unemployment would affect unemployment duration (the so-called hysteresis effects). An increasing unemployment rate may reduce a worker's chances of re-employment more the longer his duration is if, as suggested by Layard *et al.* (1991, p. 365), it raises the share of recently unemployed workers in the total pool of the unemployed and these workers are more attractive to employers than the

[5]However, Burdett (1981) shows that a sufficient condition for higher job availability reducing expected unemployment duration is a "log-concave" probability density function of wage offers.

[6]Also note that, in the macro literature on gross labor flows, Blanchard and Diamond (1990) have found that in the US job destruction is much more cyclical than job creation, and that the absolute flow from unemployment to employment does actually increase in recessions –although their computed hazard rate from unemployment is procyclical–.

longer-term unemployed. This *ranking* behavior of firms, proposed by Blanchard and Diamond (1994), could arise, e.g., if human capital loss increases with unemployment duration. We explore these issues empirically for our sample of Spanish men below.

3 Institutional features and data description

3.1 Institutional features

3.1.1 The unemployment benefit system in Spain

As in most European countries, unemployment benefits in Spain are of two types (the details are in Appendix 1). The unemployment insurance system (UI, *Sistema contributivo*) pays benefits to workers who have previously contributed when employed. They must have been dismissed from a job held at least for one year. The replacement ratio is currently equal to 70% of the previous wage during the first six months of unemployment and 60% thereafter, subject to a floor of 75% of the minimum wage and to ceilings related to the number of dependants. Benefit duration is equal to one-third of the last job's tenure, with a maximum of two years. The system's generosity was reduced in April 1992 (see Table A1) and again in 1993 (before the latter date, the minimum benefit was equal to the minimum wage and benefits were tax-exempt).

The unemployment assistance system (UA, *Sistema asistencial*) grants supplementary income to workers who have exhausted UI benefits or who do not qualify for receiving them, with dependants, and whose average family income is below 75% of the minimum wage. It pays precisely that amount, for up to two years. From 1989 onwards more generous conditions were granted to workers aged 45 or older, and benefits were extended until retirement age for workers aged 52 or older who qualify for retirement except for their age (see Table A2). The system was made more generous in 1992, but less generous in 1993 (at the latter date, the changes were as in UI). Lastly, there are special UA benefits for temporary agricultural workers in the Southern regions of Andalucía and Extremadura. Workers get 75% of the minimum wage for 90 to 300 days within the year –depending on their age and number of dependants–, as long as they have been employed for at least 40 days (20 days if they were in the system already in 1983).

Going now beyond the institutional setting, the actual coverage of unemployment benefits has increased in our sample period, from 35% of the unemployed in 1987 to 55% in 1993, with a secular decline in the share of workers in UI as a proportion of benefit recipients, which goes from 54% to 50% over the same period (Toharia (1995)). For the population we analyze in this paper, men between 20 and 64 years old, the coverage is larger, around 67% in 1992:IV, for example; and the proportion of workers on UI is slightly lower, 48%.[7]

3.1.2 Fixed-term labor contracts

A key institutional change may have affected unemployment duration in Spain within our sample period. At the end of 1984 new fixed-term contracts were introduced, which could be signed for six months[8] up to three years, and which entailed lower firing costs than the traditional permanent contracts (12 days of wages per year of service as opposed to 20 days if the permanent employee's dismissal is ruled *fair* in court or 45 days if ruled *unfair*). This change caused a swift increase in the proportion of temporary employees, from 15% in 1987 to 34% in 1994. The rate is slightly lower among men (32% in 1994), higher among the young (58% for those aged 20-29), and

[7] The data actually refer to the 20-59 year-old group, due to data availability.

[8] In April 1992 this minimum was raised to one year.

higher in agriculture and construction (around 58%) than in industry and services (around 28%). The temporary employment rate grew steadily over the sample period. The most direct impact of this change has been an increase in labor turnover rates. We estimate the impact of temporary employment on unemployment outflow rates in section 5.

3.2 The data

The data we use come from the recently released rotating panel of the Spanish Labor Force Survey (*Encuesta de Población Activa: Estadística de Flujos* (EPA)). The EPA is conducted every quarter on all members of around 60,000 households. One sixth of the sample is renewed quarterly and hence we can observe the labor market situation of an individual for up to six quarters. Some retrospective questions such as, for example, how long the individual has been in the current job, or how long he has been looking for one, are also asked.

The EPA started in its current form in 1987:II and we use the waves up to 1994:III. These 30 quarters span a complete cycle of the Spanish economy. This data set therefore has two important features. First, we can observe *entrants* into unemployment, which avoids stock sample biases. Second, we observe entrants over an extended period of time. This allows us to study the influence of personal characteristics, in particular of benefit duration, taking into account changes in aggregate conditions, so that we can assess the relative importance of these factors.

The unemployed are asked each quarter whether they are receiving any unemployment benefits (without distinguishing between UI and UA). From their answers we construct a duration of benefits variable, which is a censored entitlement to benefits variable since it only coincides with entitlement for workers with longer unemployment duration than benefit duration. There is no information on the level of benefits.

In contrast to the cross-sectional EPA, the rotating panel –as currently released– only includes individuals over 16 years of age and does not provide information on region of residence or family situation (except for marital and head-of-household status). Given this fact, we have focused on men, since for understanding married women's behavior it is particularly important to know the labor market situation of their husbands and the number and age of their children. We also exclude from our sample men aged 16 to 19 years old, given the instability of their attachment to the labor market, and men aged 65 or older, due to the importance of transitions to retirement at those ages. This leaves us with men aged 20 to 64.[9]

Our initial sample included 1,636,094 men. After filtering the sample (see Appendix 2) we obtain 60,036 unemployment spells of which 27,382 are for entrants into unemployment, that is, people actually interviewed during the quarter in which their spell started. Of those entrants only 1.37% are individuals without previous work experience. Since these are a tiny group for which sectoral variables are not available, they are excluded from the sample in the econometric estimation. Sample frequencies of individual variables are provided in Tables A3 and A4.

We consider as unemployed a broader group than the one defined by the standard LFS definition. We exclude those individuals we take as being genuinely out of the labor force, namely those who declare themselves as either being out of the labor force throughout the observed period, being a full-time student, or having no work experience and not to be looking for a job. But we include as being unemployed those classified as out of the

[9]The aggregate unemployment rate of men aged 20 years old or more, over the period 1987-1994, was 14%.

labor force during some quarters, which is not unreasonable having excluded women. An advantage of this criterion is that the transitions we look at are always from unemployment (or non-employment) to employment, rather than to non-participation.

3.3 A first look at empirical hazards, the business cycle, and benefits

We can get a first impression of the influence of the business cycle on the probability of leaving unemployment by examining the evolution over time of the sample probability of finding a job. Namely, for each quarter we evaluate the ratio of the number of individuals who find a job during that quarter to the total number of unemployed at the beginning of the quarter. This probability is displayed in Figure 1. It clearly mimics the pattern of Spanish economic activity, as captured by the quarterly growth of GDP line in the graph.

Turning to the effect of benefit receipt, and for the reasons discussed above, we now restrict the sample to include only individuals who are observed when entering unemployment. To examine this issue, we look at empirical hazards. The empirical hazard for a given number of months is the proportion of individuals unemployed for *at least* that number of months who find employment in *exactly* that number of months.

In Figure 2 we represent the hazards for workers receiving and not receiving benefits. The latter includes workers who never received benefits and also those who received them at some point, but for a period shorter than the unemployment spell length under consideration.[10] Up to the ninth month of unemployment, individuals not receiving benefits have a significantly higher

[10] Empirical hazard rates for workers who never received benefits only (not shown) are very similar to the no-benefits line in Figure 2.

hazard than those receiving benefits, and markedly so during the first five months. In addition, we present in Figure 3 the hazards for the group of men aged 30 to 44, previously employed in the construction sector, and without a university degree. This is a relatively homogeneous group and hence the comparison of the two hazard lines provides more robust evidence of the effect of benefits. As Figure 3 shows, for the first six months of the unemployment spell the difference between the hazards for workers with and without benefits is large. For example, an individual without benefits who has remained unemployed for at least three months has a probability of leaving unemployment during his third month of unemployment of 25%, as opposed to only 11% for a comparable individual receiving benefits.

A feature of the data revealed by Figures 2 and 3 is that the difference between the two empirical hazard lines (associated with a certain characteristic, in this case receiving *versus* not receiving benefits) is not constant. As a result, it will be important to allow for interactions between duration dependence and benefit status in the specification of the empirical models in the next section.

The observed decreasing pattern in aggregate hazards (as in Figure 2) is partly due to the aggregation of groups of individuals with different exit rates. Once we estimate an econometric model controlling for personal characteristics, we should be able to separate out effects on the hazards due to observed heterogeneity from those due to a combination of genuine state dependence and unobserved heterogeneity (such as variation in family income or in unobserved human capital).

4 Empirical models and econometric techniques

4.1 Basic models

The individuals in our dataset are asked for up to six consecutive quarters whether they are employed or not, and how many months they have been in the current state. They are also asked whether they are currently receiving unemployment benefits or not. From this information we can construct complete or incomplete unemployment durations (in months) for individuals *entering* unemployment at the time of the first interview or later. Individuals who abandon the sample are supposed to do so at the end of the quarter covered by the interview. This allows us to calculate monthly empirical hazards on the basis of complete durations of entrants and the surviving non-censored samples for up to 17 months. Our information also lets us construct the duration of benefit entitlement for individuals whose unemployment duration exceeds their benefit duration. Otherwise, we only observe the event that benefit entitlement is at least as long as unemployment duration. In our analysis we treat unemployment duration (T) and benefit entitlement duration (B) as discrete random variables that are subject to censoring. Unemployment duration is right censored when the individual is still unemployed at the time of leaving the sample. Benefit entitlement duration has a different type of censoring since its observability depends on it being shorter than unemployment duration.

Let C be the number of periods the individual is in the sample. In our database C is at least 2 quarters but not greater than 6 quarters. We observe T if $T < C$, otherwise we only observe the event that $T \geq C$. Moreover, we observe B if $B < T < C$. We assume that T and B are independent of C, which is not an unreasonable assumption.

This observational plan motivates us to use, as the basis for our empirical analysis of the relationship between T and B, the following hazard functions:

$$\phi_0(t) = P(T = t \mid T \geq t, B < t, C > t)$$

$$\phi_1(t) = P(T = t \mid T \geq t, B \geq t, C > t)$$

The function $\phi_0(t)$ gives the probability of being unemployed for exactly t months relative to the group of individuals who have been unemployed for at least t months and do not receive benefits at t. On the other hand, $\phi_1(t)$ gives a similar probability for individuals who are unemployed for t periods or more, but are still receiving benefits at t.

The comparison between $\phi_0(t)$ and $\phi_1(t)$ provides a meaningful basis for studying a causal effect of B on T because both probabilities are conditional upon being unemployed for t periods. In effect, regression or correlation analysis between T and B would be difficult to interpret in causal terms. The reason is that the limitation in time of benefit entitlement creates an association between being on benefits and observing shorter unemployment durations which is unrelated to the causal effect of substantive interest. Since C is independent of T and B, in what follows the conditioning on $C > t$ is omitted to simplify the presentation.

In order to clarify the nature of our analysis, let us discuss how we would proceed if we could observe benefit entitlement for all workers. If entitlement were not a censored variable at $B \geq T$, the following conditional hazard functions would be identified for any entitlement s:

$$h(t, s) = P(T = t \mid T \geq t, B = s)$$

In our dataset $h(t, s)$ is identified for $s < t$ but not for $s \geq t$. For example, with B=3, $h(1, 3), h(2, 3)$, and $h(3, 3)$ are not identified. So we cannot observe how the hazard rate for workers with benefits changes as the time of benefit exhaustion approaches.

A simple but restrictive specification under which knowledge of $\phi_0(t)$ and $\phi_1(t)$ suffices to determine $h(t,s)$ is to assume that at any t there are only two possible hazard rates depending on whether individuals receive benefits or not, for example because there are only two search intensities. In other words:

$$h(t,s) = \begin{cases} \phi_1(t) & for \quad s \geq t \\ \phi_0(t) & for \quad s < t \end{cases}$$

This *two-regime* hazard model is a restricted version of the standard model described in section 2. The latter predicts that, for two individuals with benefits at a given t, the one with shorter benefits has a greater hazard than the one with longer benefits, whereas the former model assumes that the two are equal. This assumption is not testable, though, because we do not observe B for individuals with $B \geq T$. We should therefore note that by looking at the effect of benefit entitlement on unemployment duration through a comparison of $\phi_0(t)$ and $\phi_1(t)$ we are likely to underestimate the effect of benefits on duration if the two-regime model does not hold. Indeed, we may expect the hazards for workers with and without benefits to begin to approach each other before benefit exhaustion, as the former change their behavior in anticipation of the arrival of the exhaustion date.[11]

Given the two-regime model it would be possible to reconstruct the conditional distributions of unemployment durations for a given level of benefit entitlement. In effect, we have:

$$P(T > t \mid B = s) = \prod_{k=1}^{t} [1 - h(k,s)] \quad (t = 1, 2, ...)$$

[11] $\phi_0(t)$ is a linear combination of the hazards $h(t, t-m)$ for $m = 1, ..., t$, and we would expect $h(t, t-m) < h(t, t-q)$ for $m < q$.

from which we could, for example, calculate the median unemployment duration for a given value of B, or changes in median duration from a change in benefit entitlement:

$$\Delta(s) = med(T \mid B = s+1) - med(T \mid B = s)$$

However the distributions $\{T \mid B = s\}$ do not really exist in our data, and they could only be identified owing to a functional form assumption like the two-regime model. Therefore, we shall emphasize in our empirical analysis the modelling of $\phi_0(t)$ and $\phi_1(t)$, for which we have direct counterparts in the data.

A minor point is that in our empirical analysis we redefine $\phi_0(t)$ as

$$\phi_0(t) = P(T = t \mid T \geq t, B < t-2)$$

to take into account that while T is observed at monthly intervals B is only observed at quarterly intervals (see Appendix 2). Obviously, this redefinition has no consequences for the relation of $\phi_0(t)$ and $\phi_1(t)$ to the two-regime model.

In addition to benefits, our analysis is also conditional on age, education, head of household status, industry, and year variables. Alternatively, year and industry dummies are replaced by aggregate and sectoral economic variables. The parametric models that we consider are logistic hazards of the form

$$\begin{aligned} \phi(t, b(t), x(t)) &\equiv P(T = t \mid T \geq t, b(t), x(t)) \\ &= F[\theta_0(t) + \theta_1(t)b(t) + \theta_2(t)x(t) + \theta_3(t)b(t)x(t)] \end{aligned} \tag{1}$$

where the new symbols are as follows. $x(t)$ is the vector of conditioning individual, sectoral, and aggregate variables, some of which are time-invariant like education, while others like the aggregate economic variables are time-varying. The variable $b(t)$ is the binary indicator of whether the individual still has benefits in t or not:

$$b(t) = \mathbf{1}(B \geq t)$$

F denotes the logistic cumulative distribution function:

$$F(u) = e^u/(1 + e^u)$$

In addition, $\theta_0(t)$ is an unrestricted parameter specific of each t that captures flexible additive duration dependence, and $\theta_1(t)$, $\theta_2(t)$, and $\theta_3(t)$ are polynomials in $log\, t$ whose purpose is to capture interaction effects between duration and conditioning variables.[12]

In our model $b(t)$ is a predetermined variable while the remaining time-varying variables in $x(t)$ are strictly exogenous. This means that the probability in (1) should be understood as being conditional on the entire path of $x(t)$ and the values of $b(t)$ up to t, but not on $b(t+1), b(t+2)$, etc. Namely we assume:

$$P(T = t \mid T \geq t, b(1), ..., b(t), x(1), ..., x(\infty)) = P(T = t \mid T \geq t, b(t), x(t))$$

We need to allow for feedback from T to $b(t)$ since we may expect that forecasts of the hazard at t would be improved by using $b(t+1)$ or other leads of the benefit indicator. Note that $b(t)$ would only be exogenous if the two-regime model were to hold.

A hazard function in which all the conditioning variables $x(t)$ are strictly exogenous corresponds to a conditional distribution of durations given the

[12]Note that $\phi(t, b(t), x(t))$ is just a common notation for $\phi_0(t, x(t))$ and $\phi_1(t, x(t))$: $\phi(t, b(t), x(t)) \equiv [1 - b(t)]\phi_0(t, x(t)) + b(t)\phi_1(t, x(t))$, where we specify $\phi_0(t, x(t)) = F[\theta_0(t) + \theta_2(t)x(t)]$, and $\phi_1(t, x(t)) = F[\theta_0(t) + \theta_1(t) + \theta_2(t)x(t) + \theta_3(t)x(t)]$.

full stochastic process for $x(t)$. By contrast, in the predetermined case we are effectively considering a sequence of hazard functions corresponding to different conditional distributions of durations. However, in the absence of unobserved heterogeneity, conditional inference is still possible, and we can rely on the same likelihood estimation criterion under both assumptions. The interpretation of the criterion, however, differs in each case: while with strictly exogenous variables the criterion below is the actual conditional likelihood of the data, with predetermined variables it can only be regarded as a partial likelihood (see Lancaster (1990, pp. 23-31) for a discussion of these issues).

A discrete duration model can be regarded as a sequence of binary choice equations (with cross-equation restrictions) defined on the surviving population at each duration. This provides a useful perspective, for both statistical and computational reasons, that has been noted by a number of authors (cf. Kiefer (1987), Narendranathan and Stewart (1993), Sueyoshi (1995), and Jenkins (1995)). It is also a straightforward way of motivating the estimation criterion for a duration model with predetermined variables.

To see this, let T_i^0 denote the observed censored duration variable, so that

$$T_i^0 = \begin{cases} T_i & \text{if } T_i < C_i \\ C_i & \text{otherwise} \end{cases}$$

and let c_i denote the indicator of lack of censoring:

$$c_i = \mathbf{1}(T_i < C_i)$$

Moreover, let Y_{ti} be a $(0,1)$ variable indicating whether the observed duration equals t or not:

$$Y_{ti} = \mathbf{1}(T_i^0 = t)$$

Then the conditional log-likelihood of the sample for Y_{ti} given $T_i^0 \geq t$ is of the form

$$L_t = \sum_{i=1}^{N} \mathbf{1}(T_i^0 \geq t) \left\{ c_i Y_{ti} \log \phi_i(t) + (1 - c_i Y_{ti}) \log[1 - \phi_i(t)] \right\}$$

where N is the number of unemployment spells in the sample, and

$$\phi_i(t) = \phi(t, b_i(t), x_i(t))$$

Combining the L_t for all observed durations, we obtain our estimating criterion, which can be written as follows:

$$\begin{aligned} L(\theta) &= \sum_{t=1}^{\tau} L_t \qquad (2) \\ &= \sum_{i=1}^{N} \left\{ (1 - c_i) \sum_{t=1}^{T_i^0} \log[1 - \phi_i(t)] + c_i \left(\sum_{t=1}^{T_i^0 - 1} \log[1 - \phi_i(t)] + \log \phi_i(T_i^0) \right) \right\} \end{aligned}$$

where θ is the vector of parameters to be estimated and τ is the largest observed duration.

We estimate θ by maximizing the partial likelihood $L(\theta)$. Notice that $L(\theta)$ is of the same form as a standard log-likelihood for censored discrete duration data with strictly exogenous variables, although with a different interpretation when conditioning on predetermined variables. In the absence of cross restrictions linking the parameters θ with those in the benefit indicator process, the partial likelihood estimates of θ will be asymptotically efficient.

4.2 Models with unobserved heterogeneity

The economic interpretation of the coefficients in model (1) in the previous section is likely to be hampered by unobserved heterogeneity. Aside from the problem of censoring in the benefit entitlement variable that we discussed above, in our sample there are unobserved differences in family income and in the amount of benefits received. Moreover, individuals with and without benefits may differ in ways that we do not observe. For example, there may be correlation between benefits and unobserved human capital variables.

Such unobserved heterogeneity is likely to bias downwards the effect of benefits on the exit rates, and to introduce spurious negative duration dependence. In the absence of better data it is unlikely that much more progress can be made on these issues. However, it is still possible to generalize the standard specification by making the analysis conditional on an unobserved variable u with a known distribution independent of the exogenous variables. Following the work of Heckman and Singer (1984), the recent econometric literature has emphasized the case where u is a discrete random variable with finite support, thus giving rise to a mixture model. This approach is attractive because it is flexible, and also because by letting the support of u grow with sample size it is possible to establish asymptotic properties for the estimators with respect to a model with an unspecified distribution for u.

Here we also follow this approach. In our case, the situation is fundamentally altered when unobserved heterogeneity is introduced, however, because we are conditioning on a predetermined variable. Unlike in the model with only strictly exogenous variables, we cannot just consider a mixture version of (2), since (2) is in our case a partial likelihood. In fact, by introducing unobserved heterogeneity, $b(t)$ becomes fully endogenous and we can no longer condition on it. We therefore proceed by specifying a reduced form process for $b(t)$ given u. In this way we can allow for unobserved heterogeneity that is correlated with benefits but uncorrelated with the exogenous variables. This procedure plays a role that is similar to selectivity corrections based on an auxiliary selectivity equation in linear models. A formalization of these issues is presented in the following subsections.

4.2.1 Unobserved heterogeneity in discrete duration models with predetermined variables

The joint distribution of the complete paths of Y_t and $b_t = b(t)$ given the paths of the strictly exogenous variables (which are omitted for simplicity) can be factorized as follows

$$f(Y_1, ..., Y_\tau, b_1, ..., b_\tau) = f_1 f_2$$

where

$$f_1 = f(Y_\tau \mid Y^{\tau-1}, b^\tau)...f(Y_1 \mid b_1)$$

$$f_2 = f(b_\tau \mid Y^{\tau-1}, b^{\tau-1})...f(b_2 \mid Y_1, b_1)f(b_1)$$

and we use the notation $Y^t = (Y_1, ..., Y_t)$ and $b^t = (b_1, ..., b_t)$.

Under strict exogeneity, that is, given Granger non-causality,

$$f_2 = f(b_1, ..., b_\tau)$$

and f_1 becomes the conditional likelihood of Y^τ given b^τ. Otherwise, it is just a partial likelihood. But in either case we can conduct inferences on the parameters in f_1 disregarding f_2, provided those parameters are identified in f_1 alone.

With unobserved heterogeneity we specify the hazard given u

$$f(Y_t \mid Y^{t-1}, b^t, u)$$

which is the object of interest. In the absence of Granger non-causality, however, the observed hazard $f(Y_t \mid Y^{t-1}, b^t)$ does not only depend on the sequence of hazards $f(Y_s \mid Y^{s-1}, b^s, u)$ up to t, but also on the sequence of distributions $f(b_s \mid Y^{s-1}, b^{s-1}, u)$ up to t. The link is made explicit by the following expression:

$$f(Y^\tau, b^\tau) = \int f(Y^\tau, b^\tau \mid u)dF(u)$$

or equivalently:

$$\prod_{t=1}^{\tau} f(Y_t \mid Y^{t-1}, b^t) \prod_{t=1}^{\tau} f(b_t \mid Y^{t-1}, b^{t-1}) =$$
$$= \int \prod_{t=1}^{\tau} f(Y_t \mid Y^{t-1}, b^t, u) \prod_{t=1}^{\tau} f(b_t \mid Y^{t-1}, b^{t-1}, u) dF(u)$$

where $F(u)$ is the cumulative distribution function of u.

4.2.2 Our log-likelihood with unobserved heterogeneity

A version of (1) allowing for unobserved heterogeneity is given by

$$\phi(t,u) = F[\theta_0(t) + \theta_1(t)b(t) + \theta_2(t)x(t) + \theta_3(t)b(t)x(t) + \theta_4(t)u]$$

In addition, we specify a logistic process for benefits as follows

$$\begin{aligned} \psi(t,u) &= P(b(t) = 1 \mid b(t-1) = 1, T \geq t, x(t), u) = \\ &= F\left[\gamma_0(t) + \gamma_1(t)x(t) + \gamma_2(t)u\right] \end{aligned}$$

The log-likelihood function takes the form

$$L_h = \sum_{i=1}^{N} \log \int \exp[\ell_{1i}(\theta,u) + \ell_{2i}(\gamma,u)] dF(u) \tag{3}$$

where

$$\ell_{1i}(\theta,u) = (1-c_i)\sum_{t=1}^{T_i^0} \log[1-\phi_i(t,u)] + c_i \left(\sum_{t=1}^{T_i^0-1} \log[1-\phi_i(t,u)] + \log \phi_i(T_i^0,u) \right)$$

and

$$\ell_{2i}(\gamma,u) = \sum_{t=1}^{T_i^0} b_{i(t-1)} \left\{ b_{it} \log \psi_i(t,u) + (1-b_{it}) \log[1-\psi_i(t,u)] \right\}$$

with $b_{i0} = 1$ for all i.

Finally, the variable u is assumed to be independent of $x(t)$ for all t, and to have a discrete distribution with finite support given by $\{m_1, m_2, ..., m_J\}$ and associated probabilities $p_1, ..., p_J$. This adds $2(J-1)$ parameters to the likelihood since the probabilities add up to one, and we assume that $E(u) = 0$ given the presence of constant terms in the model.

5 Empirical results

We now estimate the influence on the hazard of leaving unemployment of individual characteristics, including whether the worker receives benefits or not, and of the business cycle, while controlling for duration dependence. We first discuss duration dependence, then take in turn the effects of individual and business cycle variables, and follow with a discussion of the results allowing for unobserved heterogeneity. The section ends with a comparison of the size of the effects of the key variables.

The estimation results are reported in Table 1. In order to check the robustness of the results, we estimate two alternative specifications of the hazard equation (1). In the first one, economy-wide and sectoral determinants are captured by including dummy variables, while in the second macroeconomic variables appear directly. The qualitative impacts of the variables on the hazards are discussed in terms of the sign and statistical significance of the estimated coefficients. The size of those impacts –discussed in the last sub-section– is measured instead by the predicted effects of changes in the variables on the hazards, which is the appropriate metric in view of both the nonlinearity of the specification and the presence of terms of interaction between variables.

5.1 Duration dependence

As already mentioned, instead of imposing a given functional form, we capture duration dependence in a very flexible way by introducing an additive dummy variable for each monthly duration. Thus, a variable labeled *Dur i* in Table 1 is equal to 1 if the hazard corresponds to a duration of unemployment of i months, and 0 otherwise. Durations of more than 14 months are treated as censored at 14 months, due to their relatively small number of observations. Additional effects of duration are captured by introducing as regressors the interactions of certain variables with logged duration (*log Dur).*

The results indicate a non-monotonic duration dependence. The typical pattern of the predicted hazard is shown in Figure 4, for a given reference group.[13] For workers without benefits, the predicted hazard is increasing up to the third month and decreasing thereafter. This shape results from the combined effects of the duration dummies and the interactions of duration with other variables. We discuss these interactions below. Here we just note that duration dependence is much less evident for workers receiving benefits: as shown in the graph, after the third month the hazard levels off, or falls mildly.

It is worth pointing out that the shape depicted by the 14 coefficients of the duration dummies can be accurately reproduced by a second order polynomial on logged duration, together with a dummy that controls for spurious accumulation points at durations 4, 7, 10, and 13, due to within-quarter rounding errors. Fitting such model by OLS to the estimated coefficients for the duration dummies in the second column of Table 1 gives:

$$\begin{aligned}\widehat{\theta}_0(t) &= -2.91 + 1.54\ (\log\ t) - 0.59\ (\log\ t)^2 + 0.10\ (\log\ t) \times r(t) \\ R^2 &= 0.954\end{aligned}$$

where $r(t)$ equals one if $t \in \{4, 7, 10, 13\}$, and zero otherwise. A likelihood ratio test statistic for these restrictions is LR=102.62, which is a large number for a chi-square with 10 degrees of freedom. The result is not surprising

[13] Heads of household aged 30 to 44, with primary education, keeping aggregate variables at their sample means, and using the estimated coefficients of the specification with economic variables in Table 1.

given the large sample size involved, but all the other coefficients in the two specifications remain virtually unchanged.

5.2 Individual characteristics

5.2.1 Unemployment benefits

It is quite evident from Figure 4 that the receipt of unemployment benefits reduces the hazard of leaving unemployment. This is in agreement with the theoretical prediction of the models introduced in section 2. Moreover, the coefficient on the benefit variable is the single most significant estimated effect in both tables and the one that produces the largest change in the hazards. The reduction in the hazard falls as duration increases (note the positive coefficient on *Benefits*$\times$*log Dur* in Table 1), closing up after one year of unemployment.

There is an additional negative effect of benefits on the hazards of workers aged 30 to 44 years old, relative to those in the two other age groups (captured by *Benefits*$\times$*Age 30-44*). Although it would be natural to interpret this finding as the result of a particularly negative impact of benefit receipt on the search intensity of mature workers, several points should be kept in mind. First, in the comparison with young workers (20-29 years old) this benefit effect is likely to be capturing as well the fact that mature workers are usually entitled to higher amounts of benefits, given their higher employment seniority and number of dependants. Second, with respect to older workers (45-64 years old) two points are relevant.[14] The expected relative amount of benefits is not obvious, since older workers are likely to claim higher seniority but a lower number of dependants (children are more likely to have left home). Also, since older workers have lower hazards than

[14] We chose the starting age for the older group at 45 because the conditions for eligibility to unemployment benefits are significantly relaxed at this age.

mature workers when not receiving benefits, it turns out that benefit receipt lowers the hazards in similar proportions for the two groups (e.g. at 3-month duration, by 49% for mature workers and 42% for older workers, cf. Figure 5 and Table A6).

5.2.2 Other characteristics

The estimated effects of other personal characteristics are quite intuitive. Starting with age, Figure 5 shows that –among benefit non-recipients– the hazards of mature workers are practically identical to those of the young but quite higher than those of older workers. As a result of the effect noted in the previous paragraph, mature workers show lower hazards than the young, among benefit recipients (see Table A6). There is also evidence of negative duration dependence for older workers (captured by *Age 45-64*$\times$*log Dur*), which seems natural for workers near retirement, though the effect is minor (presumably due to the presence of the youngest workers in this age band).

As to education, holding a university degree increases the hazard only at the beginning of a spell. After the third month, the presence of negative duration dependence (captured by *University education*$\times$*log Dur*) reduces the hazards of college graduates below those of less educated workers, which presumably reflects the former's higher reservation wages. A secondary education degree does not raise the hazards significantly. Lastly, being a head of household does increase the chances of re-employment, with the effect diminishing over time (see Table A6 for both features).

5.3 Business cycle

As explained in section 2, search theory provides ambiguous predictions on the sign of the relationship between the business cycle and re-employment hazards, and the existing empirical results have also gone either way. On the other hand, Figure 1 suggests a positive relationship in our data.

Aggregate effects are measured alternatively by dummies and macroeconomic variables. In the first specification in Table 1 they are captured by sectoral, yearly, and seasonal dummies.[15] The yearly dummies are significant –the reference year being 1987– and indicate that hazards are higher for expansion years (1988-91) than for recession years (1992-94). These dummies, however, are probably also capturing the changes in the legislation in 1992-93 which made unemployment benefits less generous overall. Additionally, the hazards appear to be higher in the second and third quarters of the year.

There also appear to be significant differences in hazards across sectors. Table A6 shows, for workers without benefits, that the time pattern of hazards is similar across sectors –maybe slightly flatter in agriculture–, but the levels are quite different. The ordering of sectors in terms of the hazard of finding a job, from highest to lowest, is: agriculture, construction, services, and industry. This order does not match very well the ranking of the sectoral unemployment rates in Spain, which over the sample period was: services (10.4%), industry (11.5%), agriculture (13.4%), and construction (20.4%). In particular, the two sectors with the lowest unemployment rates show the lowest hazards of leaving unemployment, and vice versa. The puzzle is resolved once we realize that we are only analyzing unemployment outflows and ignoring inflows. The outflow ordering we have obtained is, on the other hand, correlated with the sectoral ranking in terms of the proportion of temporary employment, as described in section 3. Thus we shall include temporary employment rates by sector as explanatory variables below.

[15] An alternative specification with quarterly dummies produces virtually identical results (see Bover *et al.* (1996)).

The last two columns in Table 1 contain the results obtained when we include macroeconomic variables rather than dummies. These variables are measured as quarterly levels (e.g. sectoral unemployment rate in 1988:II) and as rates of change from same quarter of the previous year (e.g. $\Delta GDP_{1988:II} = GDP_{1988:II} - GDP_{1987:II}$).[16] The only economy-wide variable included is the rate of growth of GDP. Figure 6 depicts the hazards for workers without benefits, evaluated at the sample mean values of the macroeconomic variables and for the same individual characteristics as in the previous figures. For comparison, the hazards are also plotted for the maximum and minimum second-quarter GDP growth rates in the period: 5.4% in 1988:II and -1.6% in 1993:II.[17] The positive effect of GDP growth on the hazards is evident, although it dies out as time passes (note the negative coefficient on $\Delta GDP \times log\ Dur$).

We also introduce the following sectoral variables, which refer to the job the worker held right before becoming unemployed: the unemployment rate, in levels and rates of change, and the temporary employment rate. The level and the rate of change of the unemployment rate are intended to measure sector-specific effects, while the interaction of the latter with individual duration should capture hysteresis mechanisms, as discussed in section 2. The reason for including the temporary employment rate was given above.

In Table 1, the sectoral unemployment rate shows the expected negative sign. Figure 7 gives an idea of size, by plotting the hazards for the average, maximum, and minimum second-quarter sectoral unemployment rates in the sample period, for benefit non-recipients. The coefficient on the change in the

[16] An alternative specification in which all quarters in a given year are assigned the same yearly average level and rate of change, respectively, produces the same results (see Bover *et al.* (1996)). Sample statistics of aggregate variables are shown in Table A5.

[17] The corresponding hazards for workers receiving benefits appear in Table A6.

sectoral unemployment rate is a composite one. The constant term should be considered jointly with the other two which capture the business cycle: GDP growth and the level of unemployment. The interaction with benefits is significant, suggesting a reduction of benefit recipients' search effort when the employment outlook becomes gloomier. The interaction with individual duration is negative and significant, which can be interpreted as favorable evidence for the idea that, when hiring, firms favor workers with lower duration. The separate effect of this interacted term is shown in Figure 8, which reveals that these hysteresis effects are not large.[18]

Lastly, the sectoral temporary employment rate attracts the expected positive sign and it is the most significant estimated aggregate effect. Its impact, plotted in Figure 9, is shown to be relatively large.[19]

5.4 Unobserved heterogeneity

We now turn to the estimation of the model for the hazard of leaving unemployment with unobserved heterogeneity presented in section 4.2, which entails endogeneizing benefit receipt. Estimates of the joint mixture log-likelihood for unemployment duration and benefit receipt, as specified in equation (3), are contained in Table 2. We did not allow any interaction of the effect of the unobserved variable u with duration. Thus, in terms of the notation of section 4.2.2, the coefficients associated with u in the unemployment and benefits hazards are, respectively, $\theta_4(t) = 1$ and $\gamma_2(t) = \gamma_2$. Moreover, we specified a distribution for u with two mass points, m_1 and

[18] Significant but small hysteresis effects were also found, in the context of wage setting in Spanish manufacturing firms, by Bentolila and Dolado (1994).

[19] In order to capture the potential effect of a change of the legislation in 1992 increasing the minimum length of fixed-term labor contracts, which may have made them less attractive for employers, we included the interaction of the temporary employment rate with a dummy variable taking the value of 1 from 1992:II on. Its coefficient was hardly significant, so we have left it out.

m_2, with probabilities p_1 and p_2. However, since $E(u) = 0$, we are effectively introducing three additional free parameters in the model: m_1, p_1, and γ_2, which, together with the 35 parameters in the unemployment hazard and the 32 parameters in the benefits process, gives a total of 70 parameters in the mixture log-likelihood.

We need not devote much effort to interpreting the estimates on benefit receipt, since this is just an auxiliary reduced-form equation. Notice that we are concerned, for the first month of unemployment, with the probability that the worker is entitled to benefits upon becoming unemployed, while in subsequent periods we have the probability that the worker is entitled to benefits given that he has remained unemployed until the current month and was entitled to benefits in the previous month. The first probability depends on eligibility rules and the remaining ones on benefit duration rules. Both types of rules, however, depend on the type of benefits received. Eligibility to unemployment insurance depends only on tenure in the previous job –since all individuals in our sample have worked before–, while for unemployment assistance it depends on the number of dependants, family income, and age (see Table A1). Some regressors are correlated with both rules in the same way. For example, the worker's age or being a head of household should be positively correlated with eligibility to both UI and UA. But for other variables the signs may differ. For example, the correlation between higher education and eligibility should be positive for UI (through longer employment tenure) but negative for UA (through higher family income).

The last two columns in Table 2 show the results for a very general specification including interactions of the regressors with unemployment duration (retaining only the significant coefficients).[20] We include as a regressor a

[20] The results from estimating the reduced form process for the benefit receipt indicator separately are very close to the ones shown in Table 2 (see Bover *et al.* (1996)).

step dummy starting in April 1992, to capture the legal change increasing the stringency of UI eligibility.[21] The results are quite intuitive and we do indeed find, in two instances, differences between the results for the first month and thereafter. According to our estimates, the conditional probability of receiving benefits: (a) increases with age (after the first month for workers aged 45-64), university education (after the second month), and head of household status, (b) falls with the sectoral proportion of temporary employment, (c) is countercyclical, and (d) fell in April 1992 for all workers. The observed counter-cyclicality probably arises from the fact that the recession period in our sample was characterized by a shake-out of older, long-tenure workers which firms intended to replace by younger workers on fixed-term contracts in the subsequent expansion.

Regarding the hazard of leaving unemployment, the results with and without unobserved heterogeneity are quite consistent. All coefficients in Table 2 have the same sign as the corresponding ones in Table 1 and they are of a similar magnitude. The only exception is the interaction of *Age 45-64* with duration, whose coefficient becomes insignificant and very close to zero. Thus, in Table 2, as in Table 1, benefit receipt reduces the hazard significantly, while GDP growth and temporary employment raise it.

Lastly, the final panel in Table 2 shows that, of the two unobserved types of workers we have allowed for, one is much more frequent (its probability being 0.96), while the other, less frequent type has a much higher constant hazard. More specifically, the estimate for m_1 is -0.23 and the implied estimate for m_2 is 5.49.

[21] A dummy starting in April 1989 interacted with *Age 45-64*, meant to capture an extension of UA eligibility for that group of workers, was not significant. This was expected, since the change mostly affected workers after having received UA benefits for at least 18 months, a duration which is absent in our data. Legislative changes in 1993 affected benefit amounts but not eligibility rules.

5.5 Discussion of the results

We end this section by discussing the relative size of the effects of several variables. Among all the variables, we now focus on the most meaningful from an economic point of view: unemployment benefits and macroeconomic variables. The size of the impact of each of the remaining personal characteristics is easily read off the corresponding graphs and tables. Comparisons of size are not straightforward, because the exact magnitudes of the effects depend on the reference group of individuals and the values of the macroeconomic variables chosen for the evaluation. We discuss the results obtained for the particular values underlying the previous graphs, which are broadly representative of our results.

The relative importance of benefit receipt and GDP growth can be gauged in the following way. Take, as the benchmark, the estimated hazards for individuals not receiving benefits, keeping the growth rate of GDP at its sample period mean (2.3%). Now consider two departures from this benchmark. The effect of benefit receipt can be measured by comparing the benchmark with the hazards for individuals receiving benefits, keeping the GDP growth rate at its mean. The effect of GDP growth can be measured by comparing the benchmark with the hazards for individuals not receiving benefits, setting the GDP growth rate at the sample period minimum (-1.6%). The first comparison was shown in Figure 4 and the second one in Figure 6. Then, according to our estimates, within the first six months of unemployment, receiving benefits implies a reduction of the monthly hazard rate ranging from 4.5 percentage points (at 6 months' duration) to 10.7 points (at 3 months). By contrast, reducing the rate of growth of GDP from the mean to the minimum reduces the predicted hazard by at most 4.3 percentage points (at 3 months). After the first six months of unemployment, the effects are quite similar.

Since the effect of hazard rates on unemployment duration is cumulative, in Figure 10 we depict the impact of benefits and the cycle in terms of rates of survival in unemployment. The figure highlights how the accumulated impact of receiving benefits is larger than that of varying GDP growth. For instance, at the end of the fourth month, the chance of remaining in unemployment is less than one-half (47.3%) in the benchmark case, it is equal to 56.2% with the lowest GDP growth rate, and it is 71.6% for workers receiving benefits. Or, put in a slightly different way, the survival rate reaches the value of one-half in about 4 months in the first case, 5 months in the second case, and 7 months in the last case.

The *ceteris paribus* clause may seem too strong for this comparison, and so we have repeated the exercise for the case when the change in the GDP growth rate comes along with the weighted average sectoral unemployment rate and its (yearly) rate of change observed in the same quarter. Table A6 shows that moving from the average to the minimum GDP growth rate with the attached level and change in unemployment does not reduce the hazards by more than 5 percentage points, a still remarkably lower impact than that of benefit receipt. Furthermore, we are measuring these differences taking a worker not claiming benefits as the benchmark. The differences would still be larger if we were to take a benefit recipient as the benchmark, since in absolute terms recipients' hazards are less affected by GDP growth than those of non-recipients (see Table A6).

We therefore conclude that, for assessing the chances of re-employment of a given individual, it appears to be much more important to know whether he is receiving benefits or not than the state of the business cycle.

Another interesting exercise refers to the effects of fixed-term contracts.

Figure 9 indicates that the predicted monthly hazard rates for the same reference worker, who was previously working in a sector with a temporary employment rate of 40%, are 2 to 6 percentage points higher than if he had been working in a sector with a temporary employment rate of 18%. The magnitude of the effect is not at all negligible.

An important caveat applies to the interpretation of the results concerning duration dependence. In spite of controlling for observed worker heterogeneity, we cannot be sure of the extent to which the pattern we have found reflects true duration dependence. In general we expect a part of the estimated duration dependence to stem from unobserved heterogeneity; in our case, for example, from differences in family income or in the actual amount of benefits received and its time pattern. As is well known, spurious duration dependence may arise from changes in the composition of the stock of unemployed as time passes.[22] We have already shown that, when unobserved heterogeneity of the type considered in section 4.2 is allowed for, the estimated effects of the key variables of interest do not vary much. Nevertheless, the basic identification problem remains. As a result, more attention should be paid to the exit rates corresponding to the first few months, since they are based on a more representative sample. For the same reason, we prefer not to put much emphasis on the disparity between the shapes of duration dependence found in the data and those predicted by the standard search model.

[22] Suppose, for instance, that there were two types of workers with different, but constant, hazards. As the high-hazard workers disproportionately leave unemployment, the proportion of the low-hazard ones in the remaining stock would increase, and this would show up as negative duration dependence.

6 Conclusions

In this paper we have investigated empirically the influence of individual characteristics and the business cycle on the probability of finding a job, with special emphasis on the effects of unemployment benefits. For this purpose we have estimated monthly discrete hazard models using duration data constructed from a rotating panel sample of unemployed men in the Spanish Labor Force Survey, for the period 1987:II-1994:III.

Our main empirical results can be summarized as follows. (a) Receiving unemployment benefits reduces the hazard of leaving unemployment. For example, at an unemployment duration of three months –when the largest effects occur–, the hazard rate for workers without benefits doubles the rate for those with benefits. (b) Hazard rates are procyclical. (c) At sample-period magnitudes, receipt of unemployment benefits affects an individual's hazard of leaving unemployment to a significantly higher degree than changes in the state of the business cycle. More specifically, again at 3-month duration, the fall in the hazard caused by the receipt of benefits is 2.5 times larger than the fall in the hazard due to a 4-point drop in GDP growth. (d) There is hysteresis, since an increasing sectoral unemployment rate reduces hazard rates more the longer is individual unemployment duration, but this effect is small. And, (e) measures which increase labor market flexibility –the introduction of fixed-term contracts in the Spanish case– raise hazard rates from unemployment into employment.

Appendix 1. Unemployment benefits in Spain

Table A1. Unemployment insurance

Maximum length		Amount		Maximum amount	
1987-1991					
Tenure	Length	Length	% Wage[a]	Dependants	% Min w
1 - 5 m	0	1 - 6 m	80%	None	170%
6-48 m	Tenure/2[b]	7 -12 m	70%	1 child	195%
$>$ 48 m	24 months	13-24 m	60%	$>$ 1 child	220%
1992-1994					
Tenure	Length	Length	% Wage[a]	Same as above	
1-11 m	0	1- 6 m	70%		
12-72 m	Tenure/3[c]	7-12 m	60%		
$>$ 72 m	24 m	13-24 m	60%		

Notes: m=months. [a]Previous wage (average of last 6 months). [b]Lengths have to be multiples of 3, so the actual formula is: 3 $\times$ integer(tenure/6). [c]The actual formula is: 2 $\times$ integer(tenure/6), so that the length is an even number.

Table A2. Unemployment assistance

Maximum length			Amount		
1987-1988					
Tenure	Length		75% of the minimum wage		
1-2 m	0				
3-5 m	Tenure				
$>$ 5 m	18 months				
1989-1994					
Tenure	Length				
1- 2 m	0		Age<45	75% Min. w	
3- 5 m	Tenure		Age≥45	1 dep.	75% min. w
6-11 m	Age<45	18 m		2 deps.	100% min. w
	Age≥45	24 m		>2 deps.	125% min. w
>12 m	Age<45	24 m			
	Age≥45	30 m[a]			

Notes: deps.=dependants, min. w =minimum wage. [a]Plus 6 additional months if they have received contributory benefits for 24 months.

Appendix 2. Database description

A Individual data

Source. Rotating panel from the Spanish Labor Force Surveys (*Encuesta de Población Activa: Estadística de Flujos*) from 1987:II to 1994:III, provided by the National Statistical Office (Instituto Nacional de Estadística (INE)).

Sample. From a sample of men of 20 to 64 years of age we exclude those

* in the military or the substitute civil service
* always employed during the observed period
* never in the labor force during the observed period
* observed only once
* with a missing interview in between two valid interviews
* who have never worked and are not looking for work
* who are full-time students (from the moment they become so)
* employed who do not answer the question about how long they have been in their current job
* unemployed (and those not in the labor force) who answer neither the question "How long has it been since your last job?" nor the question "How long have you been looking for a job?"
* unemployed who do not answer the question about their relation with the public employment office (INEM)
* unemployed for over eight years.

60,036 unemployment spells satisfy these restrictions. Restricting the sample to those unemployed observed when entering unemployment leaves 27,382 spells of unemployment. Finally, at the estimation stage we drop 376 spells (1.37%) for which the information on economic sector at the previous job is lacking.

Unemployment duration. Both the unemployment and the benefit duration variables are measured in months, the smallest unit allowed by the data. The length of unemployment spells is determined using quarterly observations on the individual's labor market status. We start from the information provided the first time he answers the question "How long has it been since your last job?" or the question "How long have you been looking for a job?". For subsequent quarters, unemployment duration is computed as initial duration plus three months, instead of taking the actual reply because sometimes it led to inconsistent sequences. Although these inconsistencies may arise from very short-term employment spells, detailed analysis of the data reveals that they are much more likely due to measurement error (note that sometimes a single person answers the survey for all household members). To determine the end of the unemployment spell we use the answer to the question "How long have you been in the current job?" given by those who are unemployed at one interview and employed at the next.

Benefit duration. Benefit duration is constructed assuming that benefits are received throughout, up to the last time the individual declares to be receiving them (from a question about his relation with the employment office). Alternatively, we could have accepted the raw quarterly information on benefit receipt. An advantage of the former, smoother measure is that it overcomes the measurement error arising from the fact that individuals often start receiving benefits with some (varying) delay due to administrative reasons.[23] In any case, for 87% of our sample of entrants into unemployment the difference between the two measures is non-existent and for over 97% the difference is of three months at most. If an individual is unemployed and receiving benefits at one interview and employed at the next, we assume his benefits duration to be at least as large as his unemployment duration.

The following dummy variables used in the estimation are taken at their values at the beginning of the unemployment spell:

Economic sector at the previous job. Grouped as agriculture (including farming and fishing), industry (including mining and manufacturing), construction, and services.

Education. Three groups: Illiterate, no schooling, and primary education; Secondary education and vocational training; and University education.

Age. The available five-year age bands are grouped further into three categories: 20 to 29 years old, 30 to 44 years old, and 45 to 64 years old.

Head of household. The variable takes the value of 1 for heads of households and 0 otherwise.

Table A3 provides the frequencies of the individual variables for the sample of 27,006 entrants into unemployment that is used in the estimation. Note that monthly frequencies show troughs at multiples of 3, in both unemployment and benefit duration. The reason is that at the first interview after workers become unemployed, most reply having been unemployed for 1 or 2 months. Few reply 3 months and hardly anybody replies 0 months. These troughs naturally translate to our estimated hazards. Table A4 gives the frequencies of a set of individual variables depending on whether workers receive benefits or not.

[23] An official document reports that this delay was of 18 days as of May 1993, and that it had been longer in previous years (Ministerio de Trabajo y Seguridad Social, 1993).

B Aggregate and sectoral variables

Proportion of temporary workers. Percentage of employees on fixed-term contracts. Source: *Encuesta de Población Activa* (EPA), INE.
Unemployment rate. Source: EPA and *Series Revisadas EPA (1977-1987)*, INE.
Gross domestic product. Constant prices. Source: *Cuentas Financieras de la Economía Española (1985-1994)*, Banco de España.

Descriptive statistics are provided in Table A5.

Table A3. Frequencies of individual variables (Sample of entrants into unemployment)

	Spells	%		Spells	%
Total number of spells	27,006	100.00			
Censored	14,625	54.15			
Non-censored	12,381	45.85			
Duration of the unemployment spell			*Censored duration of benefits*		
			No benefits	13,464	49.86
1 month	4,255	15.76	1 month	1,594	5.90
2 months	3,986	14.76	2 months	1,988	7.36
3 months	2,764	10.23	3 months	1,229	4.55
4 months	3,540	13.11	4 months	1,988	7.36
5 months	2,831	10.48	5 months	1,650	6.11
6 months	1,199	4.44	6 months	644	2.38
7 months	1,923	7.12	7 months	1,072	3.97
8 months	1,595	5.91	8 months	860	3.18
9 months	580	2.15	9 months	305	1.13
10 months	1,072	3.97	10 months	563	2.08
11 months	924	3.42	11 months	492	1.82
12 months	256	0.95	12 months	131	0.49
13 months	578	2.14	13 months	292	1.08
14 months	589	2.18	14 months	275	1.02
15 months	144	0.53	15 months	73	0.27
16 months	407	1.51	16 months	201	0.74
17 months	363	1.34	17 months	185	0.69

Table A3. Frequencies of individual variables (Sample of entrants into unemployment) (contd.)

	Spells	%		Spells	%
Head-of-household status			*Economic sector at previous job*		
Head of household	14,175	52.49	Primary	5,811	21.52
Not h. of household	12,831	47.51	Construction	7,887	29.20
			Industry	5,029	18.62
Age			Services	8,279	30.66
20 to 29 years old	11,131	41.22	*Year*[a]		
30 to 44 years old	8,334	30.86			
45 to 64 years old	7,541	27.92	1987	2,282	
			1988	3,824	
Education			1989	4,112	
			1990	4,364	
Primary education or less	16,545	61.26	1991	4,423	
			1992	4,941	
Secondary education	9,680	35.84	1993	5,975	
University education	781	2.89	1994	4,503	

[a] Number of people who are unemployed in at least one month of the corresponding year (percentages not shown due to overlap among years).

Table A4. Frequencies of individual variables according to benefit receipt (%)

	Receiving benefits	Not receiving benefits
Age		
Age 20-29	37.26	45.19
Age 30-44	33.64	28.07
Age 45-64	29.10	26.74
Education		
Primary education or less	63.88	58.63
Secondary education	33.75	37.95
University education	2.37	3.42
Head of household status		
Head of household	57.24	47.71
Not head of household	42.76	52.29
Economic sector at previous job		
Primary	22.17	20.86
Construction	31.10	27.30
Industry	19.86	17.38
Services	26.88	34.45

Table A5. Sample statistics of economic variables across spells (%)

	Mean	St. dev.	Min.	Max.
Sectoral variables				
Temporary employment rate	39.28	14.50	10.98	60.49
Unemployment rate (level)	14.70	5.93	7.99	31.50
Unemployment rate (rate of change)	8.26	18.14	-36.30	60.00
National variables				
Gross domestic product (rate of change)	2.31	2.38	-1.59	6.13

Appendix 3. Additional empirical results

Table A6. Predicted hazards for different population groups and aggregate variables' values[a]

Variable	Group	Unempl. duration (months)				
		1	3	7	10	14
Age	20-29	3.7	13.1	12.7	11.9	5.7
(with benefits)	30-44	3.2	11.4	11.1	10.3	4.9
	45-64	2.4	7.2	5.9	5.1	2.2
Education	Primary	11.9	22.3	14.6	11.4	4.6
(without benefits)	Secondary	12.3	22.9	15.0	11.8	4.7
	University	15.3	23.1	13.0	9.4	3.5
Head of household	Not h. of h.	7.6	17.1	12.3	10.0	4.2
(without benefits)	Head of h.	11.9	22.3	14.6	11.4	4.6
Sector	Agriculture	10.4	29.4	27.1	24.9	12.6
(without benefits)	Construction	13.7	26.9	19.0	15.4	6.5
	Industry	11.9	22.3	14.6	11.4	4.4
	Services	10.0	21.5	15.6	12.7	5.4
GDP growth	-1.6%	1.7	8.6	10.3	10.5	5.4
(with benefits)	2.3%	2.5	11.0	12.2	12.0	6.1
	5.4%	3.4	13.3	13.9	13.4	6.7
Cycle[b]	Recession	7.0	16.8	12.4	10.3	4.3
(without benefits)	Average	9.9	21.7	16.0	13.2	5.6
	Expansion	13.1	26.3	19.1	15.6	6.6

Notes:
[a] Source: Table 1, second specification.
[b] Definitions (u=sectoral unemployment, all variables in percentages):

	ΔGDP	u	Δu
Recession	-1.6	19.2	35.0
Average	2.3	14.9	8.9
Expansion	5.4	12.4	-1.2

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Table 1. Estimates of logistic hazard of leaving unemployment

	With dummies		*With economic variables*	
Variable	Coeff.	t-ratio	Coeff.	t-ratio
Individual characteristics				
Benefits	-1.244	25.32	-1.262	25.57
Benefits × log Dur	0.572	18.44	0.581	18.73
Benefits × Age 30-44	-0.183	4.42	-0.185	4.45
Age 30-44	0.030	0.94	0.030	0.92
Age 45-64	-0.434	7.20	-0.479	8.00
Age 45-64 × log Dur	-0.210	5.47	-0.168	4.42
Secondary education	0.035	1.46	0.022	0.92
University education	0.286	2.29	0.320	2.60
Univ. education × log Dur	-0.218	2.45	-0.266	3.05
Head of household	0.496	9.91	0.505	10.13
Head of household × log Dur	-0.153	4.67	-0.164	5.03
Sectoral and time dummies				
Construction	0.308	5.22	–	–
Construction × log Dur	-0.393	9.99	–	–
Industry	0.149	2.17	–	–
Industry × log Dur	-0.475	10.34	–	–
Services	-0.053	0.85	–	–
Services × log Dur	-0.333	8.13	–	–
1988	0.124	2.59	–	–
1989	0.126	2.65	–	–
1990	0.184	3.87	–	–
1991	0.136	2.85	–	–
1992	-0.151	3.17	–	–
1993	-0.292	6.18	–	–
1994	-0.184	3.62	–	–

Table 1. Estimates of logistic hazard of leaving unemployment (contd.)[a]

Variable	*With dummies* Coeff.	*With dummies* t-ratio	*With economic variables* Coeff.	*With economic variables* t-ratio
Economic variables				
ΔGDP	–	–	9.784	6.26
ΔGDP × log Dur	–	–	-2.528	2.40
Sectoral unemployment rate	–	–	-2.366	9.72
ΔSectoral unemployment rate	–	–	0.557	2.65
ΔSectoral unempl. rate × Benefits	–	–	-0.667	5.79
ΔSectoral unempl. rate × log Dur	–	–	-0.296	2.08
Temporary employment rate	–	–	1.844	20.33
Second quarter	0.135	5.04	0.136	5.08
Third quarter	0.106	3.84	0.120	4.40
Fourth quarter	0.021	0.72	0.053	1.91
Duration dummies				
Dur 1	-2.936	40.37	-2.874	61.42
Dur 2	-2.124	35.79	-2.280	58.89
Dur 3	-1.500	27.35	-1.773	50.06
Dur 4	-1.412	25.65	-1.768	48.73
Dur 5	-1.587	26.73	-2.013	49.41
Dur 6	-1.627	25.78	-2.104	46.76
Dur 7	-1.486	22.89	-2.008	43.32
Dur 8	-1.690	23.34	-2.258	41.53
Dur 9	-1.689	21.57	-2.285	37.50
Dur 10	-1.545	19.25	-2.172	34.82
Dur 11	-1.877	19.86	-2.548	32.40
Dur 12	-2.002	18.27	-2.695	28.23
Dur 13	-1.884	16.88	-2.597	26.73
Dur 14	-2.322	15.95	-3.059	22.74

Notes: No. of spells: 27,006. Log-likelihood: First specification, -39,506.77; second specification, -39,581.02.

Table 2. Joint estimates of logistic hazards for leaving unemployment and for benefits, with unobserved heterogeneity

Variable	*Leaving unemployment* Coeff.	*t*-ratio	*Benefits process* Coeff.	*t*-ratio
Individual characteristics				
Benefits	-1.288	15.93	–	–
Benefits × log Dur	0.594	12.43	–	–
Benefits × Age 30-44	-0.199	4.50	–	–
Age 30-44	0.022	0.62	0.161	4.60
Age 30-44 × log Dur	–	–	0.110	2.52
Age 45-64	-0.711	7.46	-0.028	0.68
Age 45-64 × log Dur	-0.043	0.77	0.185	3.68
Secondary education	0.023	0.91	-0037	1.38
University education	0.475	2.62	-0.301	3.99
Univ. education × log Dur	-0.350	2.92	0.236	2.09
Head of household	0.680	8.86	0.348	10.63
Head of household × log Dur	-0.260	5.60	0.099	2.35
Economic variables				
ΔGDP	11.415	5.29	-2.314	2.07
ΔGDP × log Dur	-3.468	2.53	–	–
Dummy 1992:II-1994:III	–	–	-0.299	6.77
Sectoral unemployment rate	-2.823	10.26	1.267	4.27
ΔSectoral unemployment rate	0.480	1.62	0.674	6.30
ΔSectoral unempl. rate × Benefits	-0.724	5.84	–	–
ΔSectoral unempl. rate × log Dur	-0.222	1.18	–	–
Temporary employment rate	2.097	19.67	0.226	2.07
Temporary empl. rate × log Dur	–	-	-0.401	3.60

Table 2. Joint estimates of logistic hazards for leaving unemployment and for benefits, with unobserved heterogeneity (contd.)

Variable	*Leaving unemployment* Coeff.	*Leaving unemployment* t-ratio	*Benefits process* Coeff.	*Benefits process* t-ratio
Seasonal dummies				
Second quarter	0.136	4.83	0.045	1.44
Third quarter	0.130	4.49	-0.022	0.71
Fourth quarter	0.052	1.76	-0.014	0.44
Duration dummies				
Dur 1	-3.931	13.07	-0.069	1.91
Dur 2	-2.202	36.91	3.347	52.25
Dur 3	-1.566	27.15	2.778	47.11
Dur 4	-1.547	26.21	4.509	35.90
Dur 5	-1.787	28.74	2.811	38.85
Dur 6	-1.874	28.63	2.426	33.57
Dur 7	-1.775	26.56	4.755	23.19
Dur 8	-2.025	27.77	2.863	27.78
Dur 9	-2.050	26.18	2.361	24.05
Dur 10	-1.937	24.26	3.905	19.20
Dur 11	-2.312	24.78	2.552	19.42
Dur 12	-2.460	22.75	2.083	16.20
Dur 13	-2.362	21.50	3.824	12.93
Dur 14	-2.823	19.58	2.521	13.06
Heterogeneity coefficients				
m_1	-0.230	5.06		
m_2	5.486			
p_1	0.960	131.10		
γ_1	-0.174	7.82		

Notes: Number of spells: 27,006. Log-likelihood: -66,312.69.

FIGURE 1

PROBABILITY OF FINDING A JOB AND GDP GROWTH

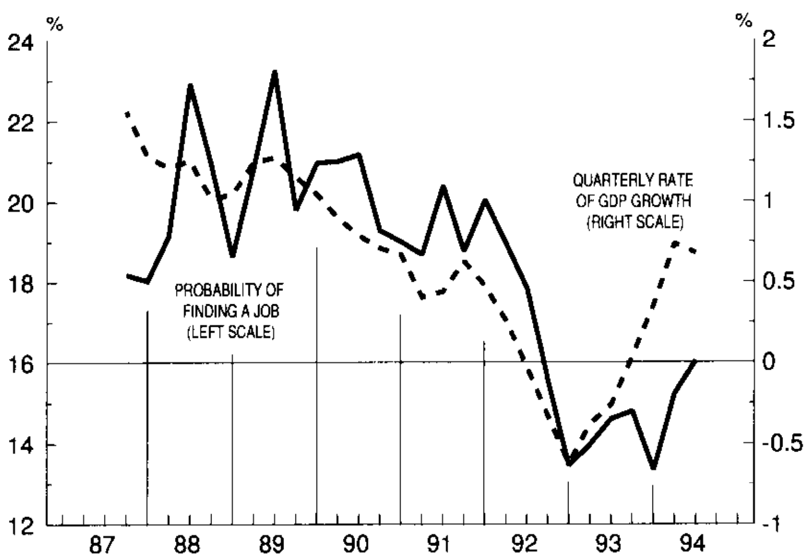


FIGURE 2

EMPIRICAL HAZARDS AND BENEFITS

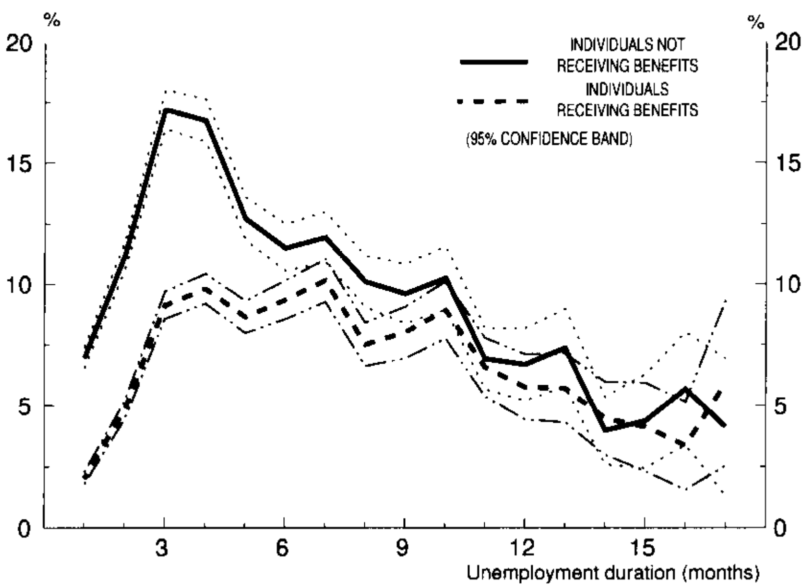


FIGURE 3

EMPIRICAL HAZARDS AND BENEFITS
(AGE 30-44, CONSTRUCTION, NON-UNIVERSITY EDUCATION)

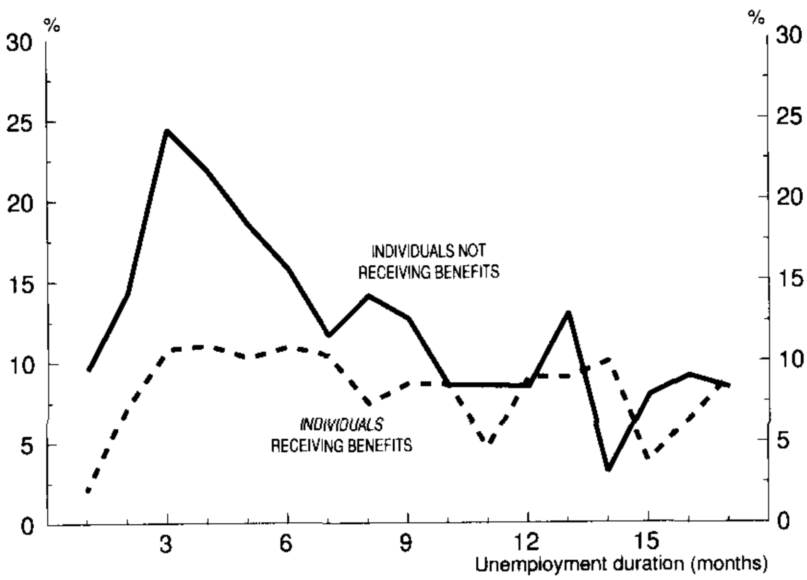
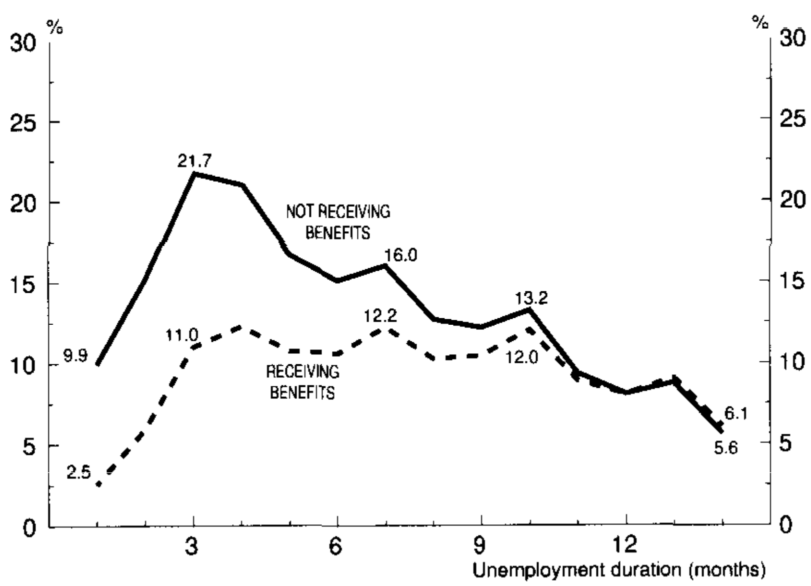


FIGURE 4

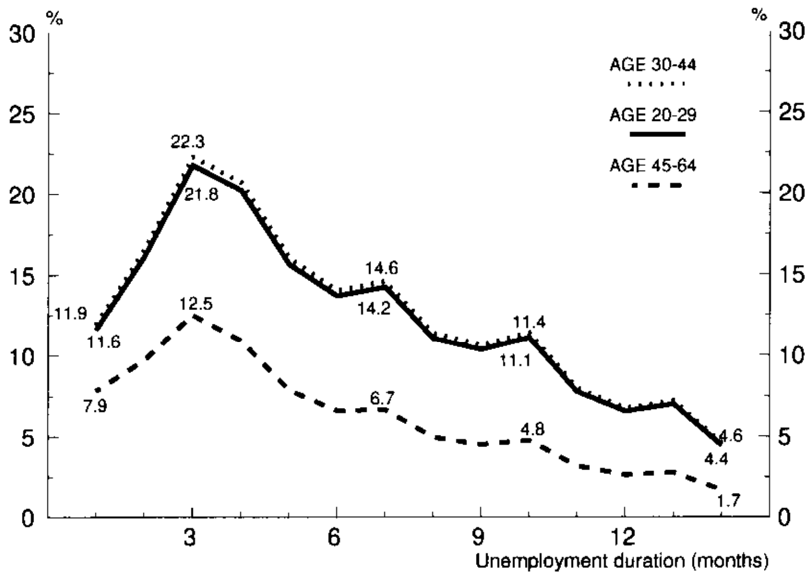
PREDICTED HAZARDS AND BENEFITS



GDP rate of growth 2.3%, sectoral unemployment rate 14.87%, rate of change of sectoral unemployment rate 8.9%, and temporary employment 39.6%.

FIGURE 5

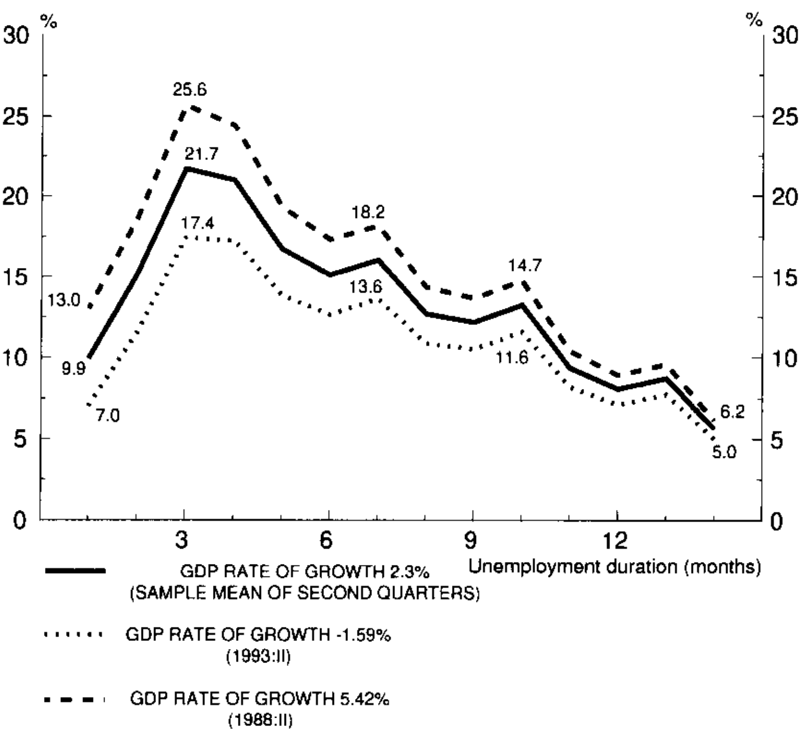
PREDICTED HAZARDS AND AGE
(NOT RECEIVING BENEFITS)



Primary education, industry, head of household, in 1989.

FIGURE 6

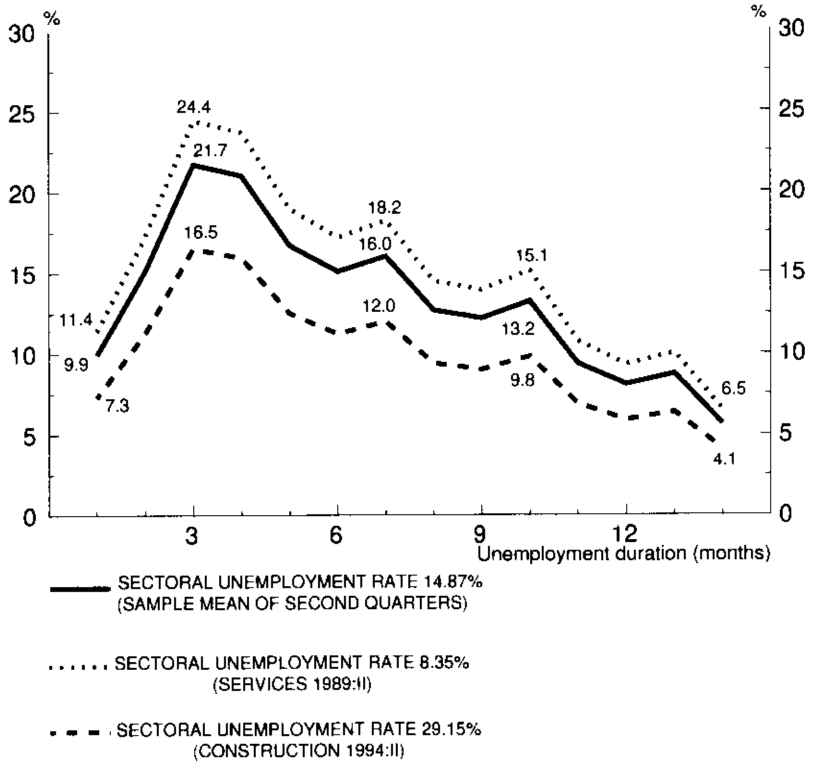
PREDICTED HAZARDS AND GDP GROWTH
(NOT RECEIVING BENEFITS)



Temporary employment 39.6%, sectoral unemployment rate 14.87%, and sectoral unemployment rate of change 8.9%.

FIGURE 7

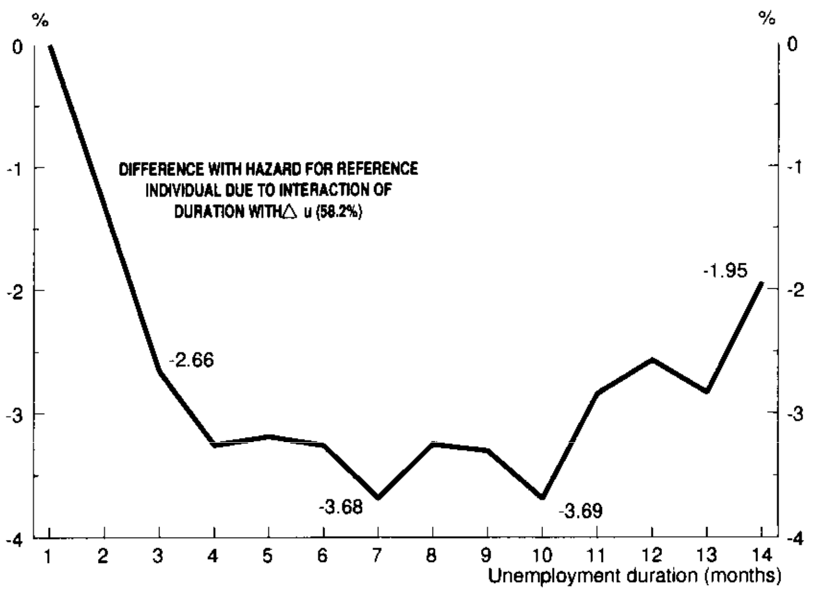
PREDICTED HAZARDS AND SECTORAL UNEMPLOYMENT (NOT RECEIVING BENEFITS)



Temporary employment 39.6%, GDP rate of growth 2.3%, and sectoral unemployment rate of change 8.9%.

FIGURE 8

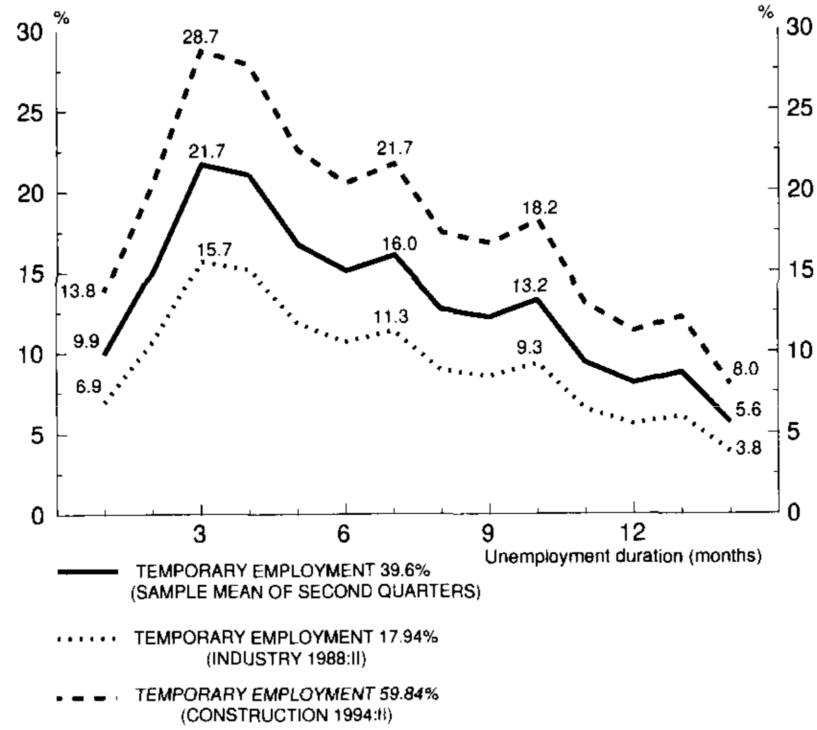
HYSTERESIS EFFECTS OF THE CHANGE IN SECTORAL UNEMPLOYMENT ON PREDICTED HAZARDS (NOT RECEIVING BENEFITS)



Temporary employment 39.6%, GDP rate of growth 2.3%, sectoral unemployment rate 14.87% and sectoral unemployment rate of change 8.9%.

FIGURE 9

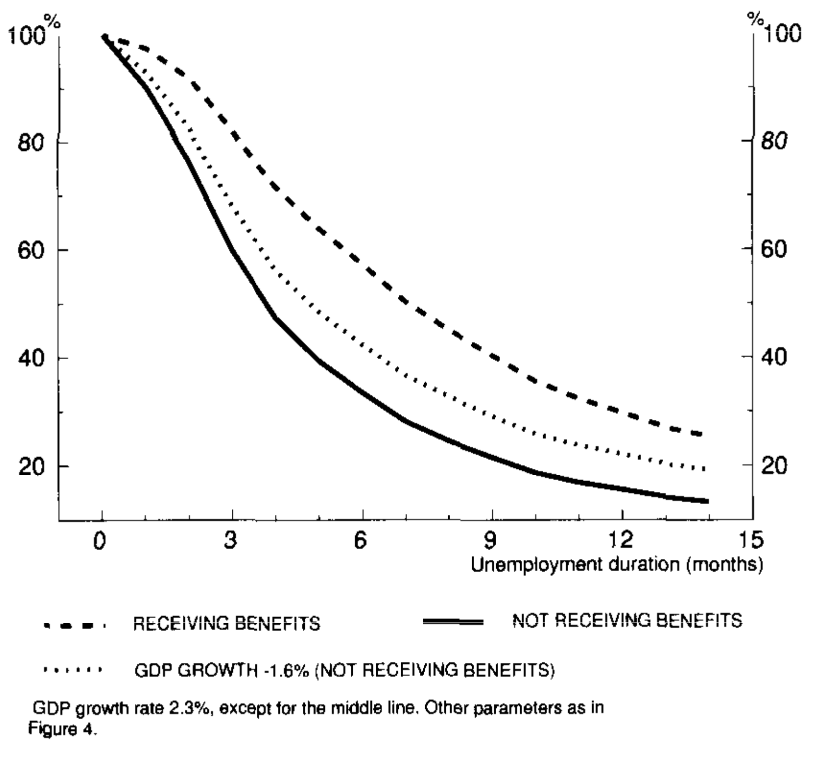
PREDICTED HAZARDS AND TEMPORARY EMPLOYMENT (NOT RECEIVING BENEFITS)



Sectoral unemployment rate 14.87%, GDP rate of growth 2.3%, and sectoral unemployment rate of change 8.9%.

FIGURE 10

SURVIVAL RATE IN UNEMPLOYMENT



GDP growth rate 2.3%, except for the middle line. Other parameters as in Figure 4.