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C O N T E N T S

INTRODUCTION (1)

Do unemployment benefits lead to longer unemployment spells? In principle we expect so, since individuals can be expected to 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.

The existing empirical evidence from US and UK microeconomic data confirms this prediction, but the estimates of the effects of benefit amounts on average unemployment duration turn out to be relatively small (2). 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, found for the US by Katz and Meyer (1990), among others (3)(4). Existing estimates of the elasticity of unemployment duration to benefits may, however, be hampered by several features of the data used in the literature. More specifically, many studies use a type of

(1) We wish to thank Daron Acemoglu, Alfonso Alba, Olivier Blanchard, Raquel Carrasco, Daniel Cohen, Jaume García, Guido Imbens, Juan Jimeno, Pedro Mira, Alfonso Novales, Steve Pischke, Enrique Sentana, Luis Toharia, José Viñals, and participants at seminars at the Banco de España and MIT for useful comments. Raquel Carrasco and Francisco de Castro provided very helpful research assistance. Any remaining errors are our own.

(2) 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 they range from 0.5 to 1 week (Narendrathan *et al.* (1985) and Lancaster and Nickell (1980), respectively). See Atkinson and Micklewright (1991) for a survey of this literature.

(3) They also estimate that an increase in benefit duration of 1 week increases average unemployment duration by 0.2 weeks.

(4) For Spain, a positive effect on duration of imputed benefit eligibility (not actual receipt, which is unobserved) has been found in a number of studies using cross-section data from a 1985 Ministry of Finance survey: Alba-Ramírez 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 steep only for those with entitlements up to 9 months. The latter three studies find small effects of the replacement ratio on the hazard of leaving unemployment.

cross-section data covering a short time period, which has several important consequences. First, the data refer to a stock of unemployed workers, which implies that there is a higher probability of sampling individuals with longer unemployment durations (the so-called *stock sampling* problem) *and* no benefits. Second, the end of a large fraction of the unemployment spells is not observed, *i.e.,* the spells are right-censored. At the estimation stage, the combination of stock sampling and censoring requires imposing non-testable assumptions on the shape of the likelihood of leaving unemployment. Third, the probability of finding a job depends on the state of the business cycle, but this type of data does not allow for a proper control of this effect (5).

In this paper we overcome some of the problems just cited by using a newly released dataset. We estimate the effects of unemployment benefit duration on unemployment duration, controlling for personal characteristics and business cycle effects, using a rotating panel sample of unemployed men from the Spanish Labor Force Survey during the period 1987:II-1994:III. The panel structure of our sample has several advantages. First, it allows us to analyze unemployment spells of entrants into unemployment, which avoids stock sample biases. Second, we observe those entrants over an extended period, which lets us reduce the extent of right-censoring, not only of unemployment spells but also of benefit durations. Third, the sample period spans a full business cycle of the Spanish economy, enabling us to take into account changes in aggregate conditions properly.

The main drawback of our dataset is that it contains no information on family income or on the actual level of benefits. 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 significantly greater effects on unemployment duration than benefit levels. For instance, 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 (6).

Since the late 1970s, 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 unem-

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(5) A few papers using longer sample periods, like Meyer (1990) or Imbens and Lynch (1994), provide estimates of business cycle effects.

(6) A related macroeconomic finding by Layard *et al.* (1991) is 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.

ployed had been such for more than a year. Since the unemployment rate depends on both inflows and outflows, studying unemployment duration alone is in general not enough to draw inferences about that rate. The analysis of outflows is, however, especially informative in Spain because —as in many other European countries— unemployment has risen more as a result of reduced outflows than of increased inflows.

Another interesting issue is the impact on unemployment duration of reforms aimed at increasing labor market flexibility. At the end of 1984 fixed-term labor contracts with much lower firing costs than those attached to permanent contracts were introduced in Spain. These contracts have been widely used, and they now comprise around one third of all employees. This institutional change contributed to a large increase in labor flows, and it should have reduced, *ceteris paribus,* unemployment duration. In this paper we test this hypothesis, obtaining favorable evidence.

As far as the empirical estimation is concerned, 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, because 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. We do so because the benefit variable in our dataset is an indicator of whether the individual is receiving benefits or not at each point in time while unemployed, which only provides censored information on benefit entitlement. 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 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 I we briefly present the predictions of standard search theory about the effects of unemployment benefits. The relevant features of the Spanish labor market institutions and our database are described in section II. In section III we discuss the empirical models and econometric techniques, and in section IV we present the empirical results. Section V contains the conclusions.

I

THEORETICAL FRAMEWORK

I.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 afterwards. 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.

I.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 (1). 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 (2). 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

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(1) 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.

(2) 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—.

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

II

INSTITUTIONAL FEATURES AND DATA DESCRIPTION

II.1. Institutional features

II.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 I). 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 % afterwards, 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 A.I.1) 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 A.I.2). 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 100 to 300 days within the year —depending on their age and number of dependants—, as long as they have been employed for at least 20 days.

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 % (1).

II.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 (2) 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 and 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 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 IV.

II.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

(1) The data actually refer to the 20-59 year-old group, due to data availability.

(2) In April 1992 this minimum was raised to one year.

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 (3).

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 A.II.1 and A.II.2.

We consider as unemployed a broader group than the one defined by the standard Labor Force Survey definition. We exclude those individuals we take as being genuinely out of the labor force, namely those who de-

(3) The aggregate unemployment rate of men aged 20 years old or more, over the period 1987-1994, was 14 %.

clare 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 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.

II.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.

Another measure of the effect of the business cycle is given by a comparison of the empirical hazards in a *good* year (for example 1989) with those in a *bad* year (for example 1992). The empirical hazard for a particular 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 those empirical hazards. Again, the importance of the business cycle is clear: unemployed workers in 1989 were much more likely to leave unemployment than those unemployed in 1992, specially at the beginning of their spell.

In order to examine the effect on empirical hazards of benefit receipt in a given month, we now restrict the sample to include only those individuals who are observed when entering unemployment, for the reasons discussed above. These hazards are represented in Figure 3. The no-benefits line 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 (4). We can see that, up to the ninth month of unemployment, individuals not receiving benefits have a significantly higher hazard than those receiving benefits, and markedly so during the first five months. In addition, we present in Figure 4 the haz-

(4) Empirical hazard rates for workers who never receive benefits (not shown) are very similar to the no-benefits line in Figure 3.

ards 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 4 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 3 and 4 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 (like in Figures 2 and 3) 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).

III

EMPIRICAL MODELS AND ECONOMETRIC TECHNIQUES

III.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:

$$\varphi_0(t) = P(T = t \mid T \geq t, B < t, C > t)$$
$$\varphi_1(t) = P(T = t \mid T \geq t, B \geq t, C > t)$$

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. Notice that $\phi_0(t)$ and $\phi_1(t)$ are linear combinations of *h(t,s):*

$$\varphi_0(t) = \frac{\sum_{s=0}^{t-1} h(t,s)\, P(T \geq t \mid B = s)\, P(B = s)}{\sum_{l=0}^{t-1} P(T \geq t \mid B = l)\, P(B = l)}$$

$$\varphi_1(t) = \frac{\sum_{s=t}^{S} h(t,s)\, P(T \geq t \mid B = s)\, P(B = s)}{\sum_{l=t}^{S} P(T \geq t \mid B = l)\, P(B = l)}$$

where *S* is the maximum value of *B.*

A simple but restrictive specification under which knowledge of $\phi_o(t)$ 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:

$$h(t,s) = \begin{cases} \varphi_1(t) \text{ for } s \geq t \\ \varphi_0(t) \text{ for } s < t \end{cases}$$

This *two-regime* hazard model is a restricted version of the standard model described in section I. 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 $B \geq T$.

Nevertheless, this model does imply some testable restrictions for our dataset. In effect, since the *h(t,s)* are identified for $t > s$, we could in principle test the hypothesis that they are all constant for any given *t.* Specifically we could test the following restrictions:

$$\begin{array}{cc} h(t,0) = h(t,1) & t = 2,\ldots,17 \\ h(t,1) = h(t,2) & t = 3,\ldots,17 \\ \vdots & \vdots \\ h(t,15) = h(t,16) & t = 17 \end{array}$$

We shall however not test these restrictions. The reason is that a priori we do not believe in the two-regime model, and so, even if the testable restrictions were accepted, we would still expect the non-testable restrictions not to hold. Instead, we shall directly model $\phi_0(t)$ and $\phi_1(t)$, which have a straightforward interpretation. 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 (1).

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:

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

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:

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

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

$$\varphi_0(t) = P(T = t \mid T \geq t, B < t - 2)$$

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 eco-

(1) As mentioned above, $\phi_0(t)$ is a linear combination of the hazards $h(t, t-m)$ for $m = 1, \ldots, t$. We would expect $h(t, t-m) < h(t, t-q)$ for $m < q$.

nomic variables. The parametric models that we consider are logistic hazards of the form

$$\varphi\left(t,\, b(t),\, x(t)\right) \equiv P\left(T = t \mid T \geq t,\, b(t),\, x(t)\right) \qquad \text{[III.1]}$$
$$= F\left[\theta_0(t) + \theta_0(t)\, b(t) + \theta_2(t)\, x(t) + \theta_3(t)\, b(t)\, x(t)\right]$$

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:

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

F denotes the logistic cumulative distribution function:

$$F(u) = e^{u} / \left(1 + e^{u}\right)$$

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 (2).

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 [III.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:

$$P\left(T = t \mid T \geq t,\, b(1), \ldots, b(t),\, x(1), \ldots, x(\infty)\right) = P\left(T = t \mid T \geq t,\, b(t),\, x(t)\right)$$

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 full stochastic process for *x(t).* By contrast, in the predetermined case

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(2) 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 $\phi_1(t, x(t)) = F\,[\theta_0(t) + \theta_1(t) + \theta_2(t)\, x(t) + \theta_3(t)\, x(t)]$.

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

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

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

$$\varphi_i(t) = \varphi(t, b_i(t), x_i(t))$$

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

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

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.

III.2. Models with unobserved heterogeneity

The economic interpretation of the coefficients in model [III.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 [III.2], since [III.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.

III.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

$$f\left(Y_1, \dots, Y_\tau, b_1, \dots, b_\tau\right) = f_1\, f_2$$

where

$$f_1 = f\left(Y_\tau \middle| Y^{\tau-1}, b^\tau\right) \dots f\left(Y_1 \middle| b_1\right)$$

$$f_2 = f\left(b_\tau \middle| Y^{\tau-1}, b^{\tau-1}\right) \dots f\left(b_2 \middle| Y_1, b_1\right) f\left(b_1\right)$$

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

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

$$f_2 = f\left(b_1, \dots, b_\tau\right)$$

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*

$$f\left(Y_t \middle| Y^{t-1}, b^t, u\right)$$

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

$$f\left(Y^\tau, b^\tau\right) = \int f\left(Y^\tau, b^\tau \middle| u\right) dF(u)$$

or equivalently:

$$\prod_{t=1}^{\tau} f\left(Y_t \middle| Y^{t-1}, b^t\right) \prod_{t=1}^{\tau} f\left(b_t \middle| Y^{t-1}, b^{t-1}\right) =$$

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

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

III.2.2. Our log-likelihood with unobserved heterogeneity

A version of [III.1] allowing for unobserved heterogeneity is given by

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

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

$$\psi(t, u) = P\left(b(t) = 1 \middle| b(t-1) = 1, T \geq t, x(t), u\right) =$$
$$= F\left[\gamma_0(t) + \gamma_1(t)\, x(t) + \gamma_2(t)\, u\right]$$

The log-likelihood function takes the form

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

where

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

and

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

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.

IV

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 some variables and a discussion of the implications for policy.

In order to check the robustness of the results, we estimate two alternative specifications of the hazard equation [III.1]. In the first one, economy-wide and sectoral determinants are captured by including dummy variables, while in the second macroeconomic variables appear directly. Furthermore, within each specification we report two alternative ways to measure aggregate variables (as explained below). Regarding individual characteristics, since the magnitudes of their coefficients are quite similar across specifications, the comments that follow refer to both of them. 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.

IV.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. For example, the variable *Dur 1* in Tables 1 and 2 is equal to 1 if the hazard corresponds to a duration of unemployment of one month, and 0 otherwise. Similarly for *Dur 2* to *Dur 14.* Durations of more than 14 months are excluded, 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 5, for a given reference group (1). For workers without benefits, the predicted hazard is increasing up to the third month and decreasing afterwards. 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.

IV.2. Individual characteristics

IV.2.1. Unemployment benefits

It is quite evident from Figure 5 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 I. 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 x log Dur* in the tables), 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 x 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,

(1) Heads of household aged 30 to 44, with primary education, keeping aggregate variables at their sample means, and using the estimated coefficients of the first specification in Table 2.

given their higher employment seniority and number of dependants. Second, with respect to older workers (45-64 years old) two points are relevant (2). 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 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 6 and Table A.III.1).

IV.2.2. Other characteristics

The estimated effects of other personal characteristics are quite intuitive. Starting with age, Figure 6 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 A.III.1). There is also evidence of negative duration dependence for older workers (captured by *Age 45-64 x 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 x 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 A.III.1 for both features).

IV.3. Business cycle

As explained in section I, 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

(2) 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.

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 Table 1 they are captured by dummies: in the first column by quarterly dummies, and in the third column by yearly plus seasonal dummies. Since the results are very close, we focus on the second alternative, which is easier to discuss. 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). The latter set of dummies, however, is 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 A.III.1 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 II. Thus we shall include temporary employment rates by sector as explanatory variables below.

Table 2 contains the estimates obtained when the dummies are replaced by macroeconomic variables. The reference periods are as follows: in the first column aggregate variables are measured by quarterly levels (e.g. sectoral unemployment rate in 1988:II) and by rates of change from same quarter of the previous year (e.g. $\Delta GDP_{1988:II} = GDP_{1988:II} — GDP_{1987:II}$); in the third column all quarters in a given year are assigned the same yearly average level (e.g. sectoral unemployment rate in 1988) and the same average yearly rate of change (e.g. $\Delta GDP_{1988} = GDP_{1988} — GDP_{1987}$). The results are again very close.

The only economy-wide variable included is the rate of growth of GDP. Figure 7 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 (3). The positive effect of GDP growth on the hazards is evident, although it dies out as time passes (note the negative coefficient on Δ *GDP x 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 I. The reason for including the temporary employment rate was given above.

In Table 2, the sectoral unemployment rate shows the expected negative sign. Figure 8 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 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 9, which reveals that these hysteresis effects are not large (4).

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 10, is shown to be relatively large (5).

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(3) The corresponding hazards for workers receiving benefits appear in Table A.III.1.

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

(5) 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.

IV.4. Unobserved heterogeneity

We now turn to the estimation of the model for the hazard of leaving unemployment with unobserved heterogeneity presented in section III.2. This model entails endogeneizing benefit receipt. Since it provides useful complementary information, before presenting the joint estimates, we briefly discuss the results of estimating a reduced form process for the benefit receipt indicator alone.

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 at 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 A.I.1). 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).

Table A.III.2 shows the results for a very general specification including interactions of the regressors with unemployment duration (retaining only the significant coefficients). We include as a regressor a step dummy starting in April 1992, to capture the legal change increasing the stringency of UI eligibility (6). The results are quite intuitive, indicating that the conditional probability of receiving benefits: (a) increases with age (after the first month for workers aged 45-64), university education (after the third month), and head of household status, (b) falls with the sectoral proportion of temporary employment (after the first month), (c) is countercyclical, and (d) fell in April 1992 for all workers. The observed countercyclicality probably arises from the fact that the recession period in our

(6) 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.

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.

Estimates of the joint mixture log-likelihood for unemployment duration and benefit receipt, as specified in equation [III.3], are contained in Table 3. We did not allow any interaction of the effect of the unobserved variable *u* with duration. Thus, in terms of the notation of section III.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 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.

The results with and without unobserved heterogeneity are quite consistent. All coefficients in Table 3 have the same sign and are of a similar magnitude as those in Table 2. The only exception is the interaction of *Age 45-64* with duration, whose coefficient becomes insignificant and very close to zero. Specifically, in Table 3 benefit receipt reduces the hazard significantly, GDP growth and temporary employment raise it. The coefficients on the jointly estimated equation for the benefit receipt indicator also have the same sign and similar magnitude to those obtained when it was estimated separately (Table A.III.2).

Lastly, the final panel in Table 3 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.

IV.5. Discussion of the results

We end this section by discussing the relative sizes of the effects of several variables and the policy implications stemming from our results. Among all the variables, we now focus on the most meaningful from an economic point of view: unemployment benefits and macroeconomic variables. The sizes of the impacts of the remaining personal characteristics are 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 by comparing Figures 5 and 7. According to our estimates, a change in the rate of growth of GDP from 2.3 % to –1.6 % (i.e. a 4-point drop) reduces the predicted monthly hazard of finding a job for a worker not receiving benefits by 4.3 percentage points, at most. In contrast, at 2.3 % GDP growth, a comparable worker who does receive benefits has a monthly hazard which is lower by 7.4 to 10.7 percentage points in the first three months of unemployment, and by 4.5 percentage points after six months. Since the *ceteris paribus* clause may seem too strong for this comparison, 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 A.III.1 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 baseline. The differences would still be larger if we were to take a recipient as the reference, since in absolute terms recipients' hazards are less affected by GDP growth than those of non-recipients (see Table A.III.1).

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 than the state of the business cycle.

Another interesting exercise refers to the effects of fixed-term contracts. Figure 10 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 (7). We have already shown that, when unobserved heterogeneity of the type considered

(7) 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.

in section III.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.

What policy implications can be derived from our results? Surely, the policy goal should be to reduce the unemployment rate, rather than increasing jobfinding rates *per se.* In the introduction we noted, though, that Spanish unemployment is, as in many other European countries, chiefly an outflow problem. This has manifested itself in a large share of long-term unemployment. These facts make a *prima facie* case for policy measures aimed at increasing re-employment probabilities. Our empirical findings indicate that lowering unemployment benefit durations would be appropriate for this purpose (8). Clearly, the extent to which this measure would translate into a reduction of the unemployment rate would depend on two key links: how much would reservation wages fall in response to a reduction in benefit duration and how much would labor demand increase in response to the drop in reservation wages. We unfortunately lack empirical evidence on these two elasticities. On the other hand, if negotiated wage settlements preclude contracting below a certain wage level, a reduction in reservation wages may have little impact on re-employment probabilities even if labor demand wage elasticities are high.

Moreover, policy decisions should be based on welfare assessments, and it is not obvious that reducing benefit duration would necessarily increase welfare. Unemployment benefits create both gains and losses. The former come in the form of smoother consumption of households with unemployed members (in the presence of risk aversion and incomplete private insurance against the unemployment risk) and of more efficient worker-firm matches. The losses, apart from longer unemployment duration and the resulting loss of human capital, may arise from lower precautionary saving, leading to lower capital stock and output. As a result, the net welfare impact of a change in benefit duration would be difficult to assess, and no established evidence is yet available [see Valdivia (1995)]. What our results show is that the desirable effects of benefits have to be traded off against the undesirable outcome of significantly larger unemployment durations.

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(8) Note that lowering benefit duration may not only raise hazard rates from unemployment but may also lower hazard rates into unemployment (not analyzed here), although the international empirical evidence suggests that this effect is relatively small [see Atkinson and Micklewright (1991)].

Lastly, the difference between affecting unemployment rates and unemployment outflow probabilities mentioned before becomes especially relevant in the case of fixed-term labor contracts. We have found that these contracts have a sizable positive effect on the hazard of leaving unemployment. On the other hand, they are almost sure to raise the hazard of entering unemployment as well, thus raising the unemployment rate. By providing workers with work habits and experience, and by mitigating adverse duration dependence effects (especially for the long-term unemployed), we could expect that the net effect of fixed-term contracts on the unemployment rate would be positive. Establishing this conjecture, however, would require an empirical assessment of the dynamics of employment and unemployment spells, which is outside the scope of this paper. Ultimately, any policy recommendation about temporary contracts cannot be dissociated from those concerning the firing costs of the alternative permanent labor contracts.

V

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.

TABLES AND FIGURES

TABLE 1

ESTIMATES OF LOGISTIC HAZARDS.
MODEL WITH TIME AND SECTORAL DUMMIES (a)

Variable	*Coeff.*	*t*	*Coeff.*	*t*
INDIVIDUAL CHARACTERISTICS:				
Benefits	–1.245	25.34	–1.244	25.32
Benefits x log Dur	0.572	18.44	0.572	18.44
Benefits x Age 30-44	–0.182	4.40	–0.183	4.42
Age 30-44	0.030	0.91	0.030	0.94
Age 45-64	–0.434	7.20	–0.434	7.20
Age 45-64 x log Dur	–0.210	5.47	–0.210	5.47
Secondary education	0.034	1.44	0.035	1.46
University education	0.290	2.32	0.286	2.29
University education x log Dur	–0.221	2.48	–0.218	2.45
Head of household	0.496	9.92	0.496	9.91
Head of household x log Dur	–0.153	4.67	–0.153	4.67
SECTORAL AND TIME DUMMIES:				
Industry	0.152	2.21	0.149	2.17
Industry x log Dur	–0.476	10.36	–0.475	10.34
Construction	0.310	5.25	0.308	5.22
Construction x log Dur	–0.394	10.01	–0.393	9.99
Services	–0.051	0.82	–0.053	0.85
Services x log Dur	–0.334	8.15	–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
SEASONAL DUMMIES:				
Second quarter	—	—	0.135	5.04
Third quarter	—	—	0.106	3.84
Fourth quarter	—	—	0.021	0.72
DURATION DUMMIES:				
Dur 1	–2.749	27.19	–2.936	40.37
Dur 2	–1.933	20.53	–2.124	35.79
Dur 3	–1.308	14.28	–1.500	27.35
Dur 4	–1.220	13.28	–1.412	25.65
Dur 5	–1.394	14.61	–1.587	26.73
Dur 6	–1.434	14.65	–1.627	25.78
Dur 7	–1.293	13.03	–1.486	22.89
Dur 8	–1.496	14.43	–1.690	23.34
Dur 9	–1.495	13.85	–1.689	21.57
Dur 10	–1.352	12.35	–1.545	19.25
Dur 11	–1.685	14.02	–1.877	19.86
Dur 12	–1.812	13.68	–2.002	18.27
Dur 13	–1.694	12.63	–1.884	16.88
Dur 14	–2.130	13.03	–2.322	15.95

(a) In the first specification quarterly dummy variables (coefficients not reported) are included in place of yearly and seasonal dummy variables.
Number of spells: 27,006.
Log-likelihood: First specification, –39,494.77; second specification, –39,506.77.

TABLE 2

ESTIMATES OF LOGISTIC HAZARDS.
MODEL WITH AGGREGATE AND SECTORAL ECONOMIC VARIABLES (a)

Variable	*Coeff.*	*t*	*Coeff.*	*t*
INDIVIDUAL CHARACTERISTICS:				
Benefits	–1.262	25.57	–1.258	25.48
Benefits x log Dur	0.581	18.73	0.580	18.69
Benefits x Age 30-44	–0.185	4.45	–0.190	4.58
Age 30-44	0.030	0.92	0.030	0.94
Age 45-64	–0.479	8.00	–0.481	8.03
Age 45-64 x log Dur	–0.168	4.42	–0.169	4.45
Secondary education	0.022	0.92	0.018	0.77
University education	0.320	2.60	0.314	2.56
University education x log Dur	–0.266	3.05	–0.265	3.03
Head of household	0.505	10.13	0.504	10.11
Head of household x log Dur	–0.164	5.03	–0.164	5.02
SECTORAL AND ECONOMY-WIDE VARIABLES:				
Δ GDP	9.784	6.26	9.662	5.35
Δ GDP x log Dur	–2.528	2.40	–2.733	2.25
Sectoral unemployment rate	–2.366	9.72	–2.379	9.73
Δ Sectoral unemployment rate	0.557	2.65	0.462	1.83
Δ Sectoral unemployment rate x Benefits	–0.667	5.79	–0.667	5.23
Δ Sectoral unemployment rate x log Dur	–0.296	2.08	–0.320	1.87
Temporary employment rate	1.844	20.33	1.827	19.96
SEASONAL DUMMIES:				
Second quarter	0.136	5.08	0.134	5.00
Third quarter	0.120	4.40	0.118	4.32
Fourth quarter	0.053	1.91	0.048	1.70
DURATION DUMMIES:				
Dur 1	–2.874	61.42	–2.868	61.36
Dur 2	–2.280	58.89	–2.274	58.81
Dur 3	–1.773	50.06	–1.768	49.98
Dur 4	–1.768	48.73	–1.764	48.67
Dur 5	–2.013	49.41	–2.007	49.30
Dur 6	–2.104	46.76	–2.099	46.67
Dur 7	–2.008	43.32	–2.003	43.24
Dur 8	–2.258	41.53	–2.251	41.44
Dur 9	–2.285	37.50	–2.281	37.45
Dur 10	–2.172	34.82	–2.170	34.79
Dur 11	–2.548	32.40	–2.540	32.32
Dur 12	–2.695	28.23	–2.691	28.18
Dur 13	–2.597	26.73	–2.593	26.70
Dur 14	–3.059	22.74	–3.056	22.72

(a) Aggregate variables: In the first specification, they are measured by quarterly levels and by rates of change from the same quarter of the previous year. In the second specification, all quarters in a given year are assigned the same yearly aerage level and the same average yearly rate of change.
Number of spells: 27,006.
Log-likelihood: First specification, –39,581.02; ssecond specification, –39,598.94.

TABLE 3

JOINT ESTIMATES OF LOGISTIC HAZARDS FOR UNEMPLOYMENT AND BENEFITS WITH UNOBSERVED HETEROGENEITY (a)

Hazard of leaving unemployment		
Variable	*Coeff.*	*t*
INDIVIDUAL CHARACTERISTICS:		
Benefits	–1.288	15.93
Benefits x log Dur	0.594	12.43
Benefits x Edad 30-44	–0.199	4.50
Age 30-44	0.022	0.62
Age 45-64	–0.711	7.46
Age 45-64 x log Dur	–0.043	0.77
Secondary education	0.023	0.91
University education	0.475	2.62
University education x log Dur	–0.350	2.92
Head of household	0.680	8.86
Head of household x log Dur	–0.260	5.60
SECTORAL AND ECONOMY-WIDE VARIABLES:		
Δ GDP	11.415	5.29
Δ GDP x log Dur	–3.468	2.53
Sectoral unemployment rate	–2.823	10.26
Δ Sectoral unemployment rate	0.480	1.62
Δ Sectoral unemployment rate x Benefits	–0.724	5.84
Δ Sectoral unemployment rate x log Dur	–0.222	1.18
Temporary employment rate	2.097	19.67
SEASONAL DUMMIES:		
Second quarter	0.136	4.83
Third quarter	0.130	4.49
Fourth quarter	0.052	1.76
DURATION DUMMIES:		
Dur 1	–3.931	13.07
Dur 2	–2.202	36.91
Dur 3	–1.566	27.15
Dur 4	–1.547	26.21
Dur 5	–1.787	28.74
Dur 6	–1.874	28.63
Dur 7	–1.775	26.56
Dur 8	–2.025	27.77
Dur 9	–2.050	26.18
Dur 10	–1.937	24.26
Dur 11	–2.312	24.78
Dur 12	–2.460	22.75
Dur 13	–2.362	21.50
Dur 14	–2.823	19.58

(a) Aggregate variables are measured as in the first specification in Table 2.
Number of spells: 27,006.
Log-likelihood: –66,312.69.

TABLE 3

JOINT ESTIMATES OF LOGISTIC HAZARDS FOR UNEMPLOYMENT AND BENEFITS WITH UNOBSERVED HETEROGENEITY (contd.)

Reduced form process for benefits		
Variable	*Coeff.*	*t*
INDIVIDUAL CHARACTERISTICS:		
Age 30-44	0.161	4.60
Age 30-44 x log Dur	0.110	2.52
Age 45-64	–0.028	0.68
Age 45-64 x log Dur	0.185	3.68
Secondary education	–0.037	1.38
University education	–0.301	3.99
University education x log Dur	0.236	2.09
Head of household	0.348	10.63
Head of household x log Dur	0.099	2.35
SECTORAL AND ECONOMY-WIDE VARIABLES:		
Δ GDP	–2.314	2.07
Dummy 1992:II-1994:III	–0.299	6.77
Sectoral unemployment rate	1.267	4.27
Δ Sectoral unemployment rate	0.674	6.30
Temporary employment rate	0.226	2.07
Temp. employment rate x log Dur	–0.401	3.60
SEASONAL DUMMIES:		
Second quarter	0.045	1.44
Third quarter	–0.022	0.71
Fourth quarter	–0.014	0.44
DURATION DUMMIES:		
Dur 1	–0.069	1.91
Dur 2	3.347	52.25
Dur 3	2.778	47.11
Dur 4	4.509	35.90
Dur 5	2.811	38.85
Dur 6	2.426	33.57
Dur 7	4.755	23.19
Dur 8	2.863	27.78
Dur 9	2.361	24.05
Dur 10	3.905	19.20
Dur 11	2.552	19.42
Dur 12	2.083	16.20
Dur 13	3.824	12.93
Dur 14	2.521	13.06
Heterogeneity coeffcients		
m_1	–0.230	5.06
m_2	5.486	
p_1	0.960	131.10
γ_2	–0.174	7.82

FIGURE 1

PROBABILITY OF FINDING A JOB AND GDP GROWTH

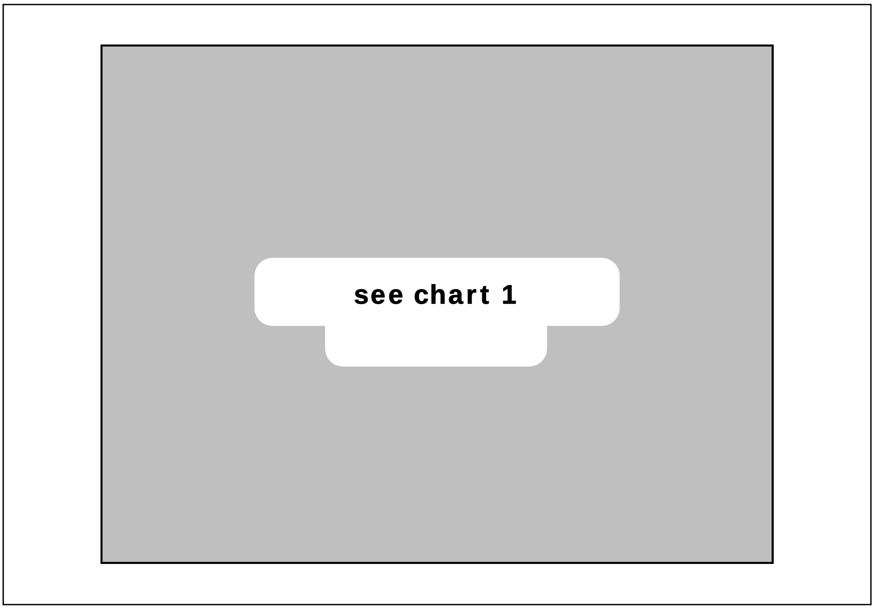

FIGURE 2

EMPIRICAL HAZARDS BY YEAR

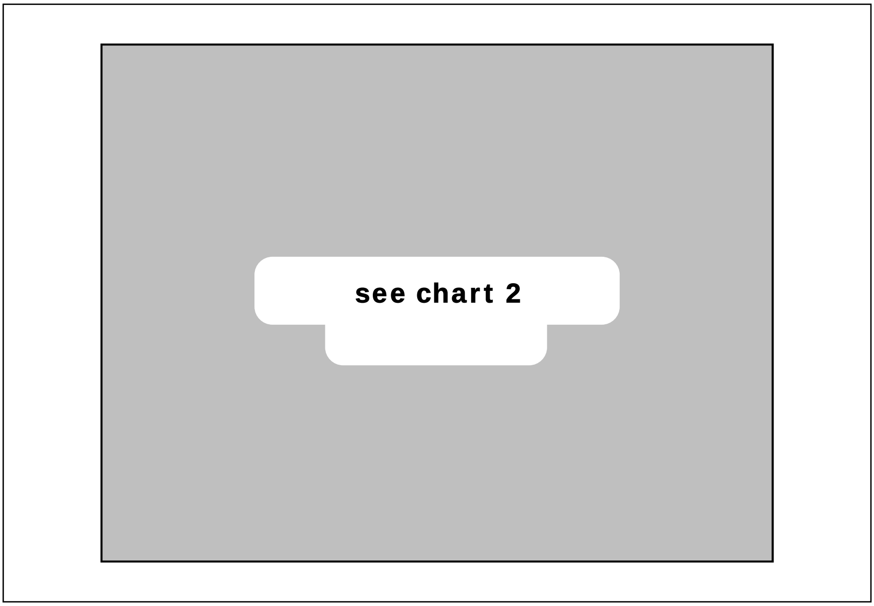

FIGURE 3

EMPIRICAL HAZARDS AND BENEFITS

see chart 3

FIGURE 4

EMPIRICAL HAZARDS AND BENEFITS
Age 30-44, construction, non-university education

see chart 4

FIGURE 5

PREDICTED HAZARDS AND BENEFITS (a)

see chart 5

(a) 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 6

PREDICTED HAZARDS AND AGE
Not receiving benefits (a)

see chart 6

(a) Primary education, industry, head of household, in 1989.

FIGURE 7

PREDICTED HAZARDS AND GDP GROWTH
Not receiving benefits (a)

see chart 7

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

FIGURE 8

PREDICTED HAZARDS AND SECTORAL UNEMPLOYMENT
Not receiving benefits (a)

see chart 8

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

FIGURE 9

HYSTERESIS EFFECTS OF THE CHANGE IN SECTORAL UNEMPLOYMENT ON PREDICTED HAZARDS
Not receiving benefits (a)

see chart 9

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

FIGURE 10

PREDICTED HAZARDS AND TEMPORARY EMPLOYMENT
Not receiving benefits (a)

see chart 10

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

APPENDICES

APPENDIX I

UNEMPLOYMENT BENEFITS IN SPAIN

TABLE A.I.1

UNEMPLOYMENT INSURANCE

Maximum length		*Amount*		*Maximum amount*	
		1984			
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			
1-11 m	0	1-6 m	70 %		
12-72 m	Tenure/3 (c)	7-12 m	60 %	Same as above	
> 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 x integer (tenure/6).
(c) The actual formula is: 2 x integer (tenure/6), so that the length is an even number.

TABLE A.I.2

UNEMPLOYMENT ASSISTANCE

Maximum length			*Amount*		
			1984		
Tenure	*Length*				
1-2 m	0				
3-5 m	Tenure		75 % of the minimum wage		
> 5 m	18 months				
			1989		
1-2 m	0		Age< 45	75 % Min. w	
3-5 m	Tenure				
6-11 m	Age < 45	18 m	Age ≥ 45	1 dep.	75 % min. w
	Age ≥ 45	24 m		2 deps.	100 % min. w
> 12 m	Age < 45	24 m		> 2 deps.	125 % min. w
	Age ≥ 45	30 (a)			

Note: deps.=dependants.
(a) Plus 6 additional months if they have received contributory benefits for 24 months.

APPENDIX II

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 (1). 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.

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(1) 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).

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 A.II.1 provides the frequencies of the individual variables for the sample of 27006 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. Fewer reply 3 months and hardly anybody replies 0 months. These troughs naturally translate to our estimated hazards. Table A.II.2 gives the frequencies of a set of individual variables depending on whether workers receive benefits or not.

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 A.II.3.

TABLE A.II.1

FREQUENCIES OF INDIVIDUAL VARIABLES
Sample of entrants into unemployment

	Number	*Percentage*
Total number of spells	**27,006**	**100.00**
Censored	14,625	54.15
Non censored	12,381	45.85
DURATION OF THE UNEMPLOYMENT SPELL:		
1 month	4,255	15.76
2 months	3,986	14.76
3 months	2,764	10.23
4 months	3,540	13.11
5 months	2,831	10.48
6 months	1,199	4.44
7 months	1,923	7.12
8 months	1,595	5.91
9 months	580	2.15
10 months	1,072	3.97
11 months	924	3.42
12 months	256	0.95
13 months	578	2.14
14 months	589	2.18
15 months	144	0.53
16 months	407	1.51
17 months	363	1.34
CENSORED DURATION OF BENEFITS:		
No benefits	13,464	49.86
1 month	1,594	5.90
2 months	1,988	7.36
3 months	1,229	4.55
4 months	1,988	7.36
5 months	1,650	6.11
6 months	644	2.38
7 months	1,072	3.97
8 months	860	3.18
9 months	305	1.13
10 months	563	2.08
11 months	492	1.82
12 months	131	0.49
13 months	292	1.08
14 months	275	1.02
15 months	73	0.27
16 months	201	0.74
17 months	185	0.69
HEAD-OF-HOUSEHOLD STATUS:		
Head of household	14,175	52.49
Not head of household	12,831	47.51

FREQUENCIES OF INDIVIDUAL VARIABLES
(contd.)

	Number	Percentage
AGE:		
20 to 29 years old	11,131	41.22
30 to 44 years old	8,334	30.86
45 to 64 years old	7,541	27.92
EDUCATION:		
Primary education or less	16,545	61.26
Secondary education	9,680	35.84
University education	781	2.89
ECONOMIC SECTOR AT PREVIOUS JOB:		
Primary	5,811	21.52
Construction	7,887	29.20
Industry	5,029	18.62
Services	8,279	30.66
YEAR (a):		
1987	2,282	
1988	3,824	
1989	4,112	
1990	4,364	
1991	4,423	
1992	4,941	
1993	5,975	
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 A.II.2

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 eduation	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 A.II.3

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

APENDIX III

ADDITIONAL EMPIRICAL RESULTS

TABLE A.III.1

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)	H. 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

(a) Source: Table 2, first specification.
(b) Definitions (u = sectoral unmeployment, 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

TABLE A.III.2

ESTIMATES OF THE REDUCED FORM PROCESS FOR BENEFITS WITHOUT UNOBSERVED HETEROGENEITY (a)

Variable	*Coeff.*	*t*
INDIVIDUAL CHARACTERISTICS:		
Age 30-44	0.156	4.51
Age 30-44 x log Dur	0.111	2.57
Age 45-64	–0.029	0.72
Age 45-64 x log Dur	0.184	3.68
Secondary education	–0.038	1.41
University education	–0.298	3.98
University education x log Dur	0.234	2.07
Head of household	0.345	10.62
Head of household x log Dur	0.101	2.41
SECTORAL AND ECONOMY-WIDE VARIABLES:		
Δ GDP	–2.186	1.97
Dummy 1992:II-1994:III	–0.281	6.40
Sectoral unmeployment rate	1.164	3.95
Δ Sectoral unemployment rate	0.667	6.27
Temporary employment rate	0.257	2.36
Temp. employment rate x log Dur	–0.404	3.63
SEASONAL DUMMIES:		
Second quarter	0.040	1.30
Third quarter	–0.023	0.73
Fourth quarter	–0.015	0.49
DURATION DUMMIES:		
Dur 1	–0.069	1.91
Dur 2	3.371	52.88
Dur 3	2.813	48.14
Dur 4	4.545	36.26
Dur 5	2.847	39.58
Dur 6	2.462	34.27
Dur 7	4.791	23.38
Dur 8	2.899	28.22
Dur 9	2.398	24.49
Dur 10	3.941	19.39
Dur 11	2.588	19.73
Dur 12	2.119	16.51
Dur 13	3.860	13.06
Dur 14	2.558	13.26

(a) Aggregate variables are measured by quarterly levels and by rates of change from the same quarter of the previous year.

Number of spells: 27,006.

Log-likelihood: –26,748.57.

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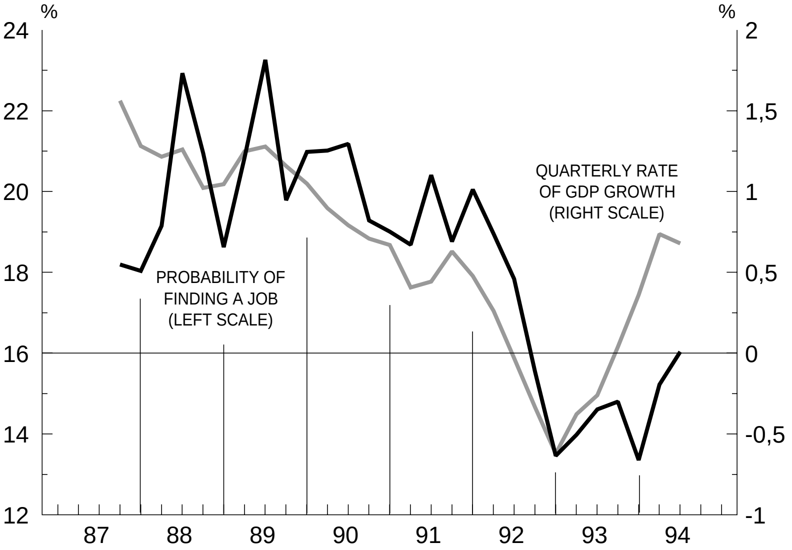
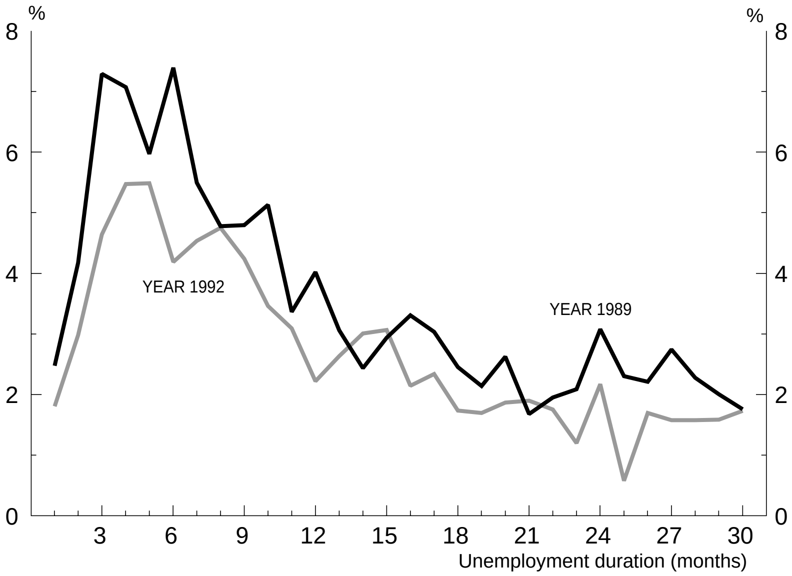
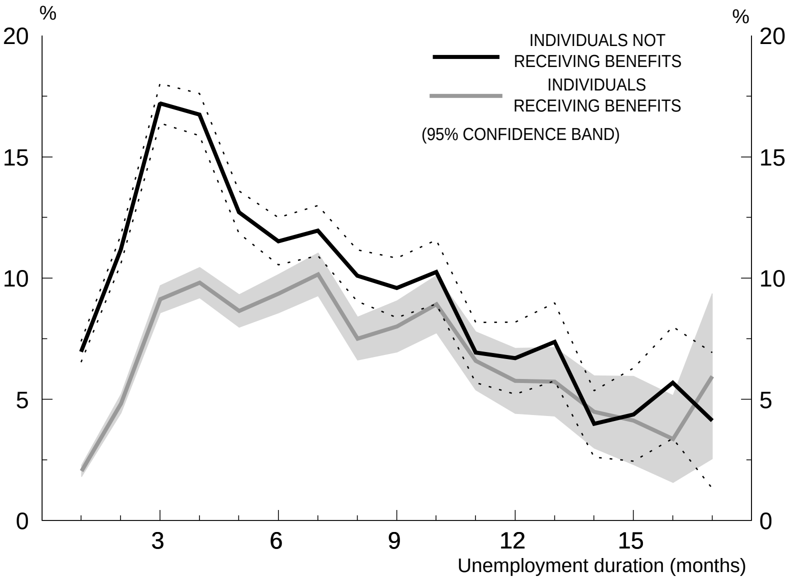
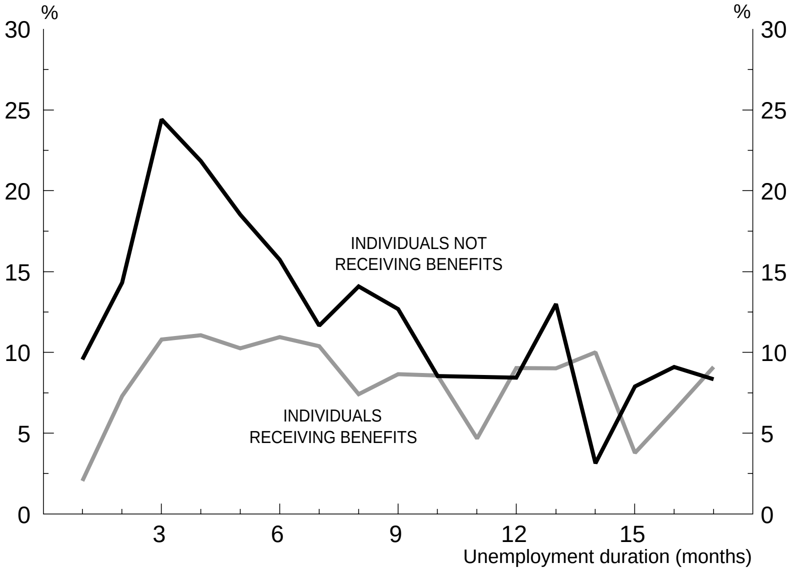

%
24
22
20
18
16
14
12
%
2
1,5
1
0,5
0
-0,5
-1
PROBABILITY OF
FINDING A JOB
(LEFT SCALE)
QUARTERLY RATE
OF GDP GROWTH
(RIGHT SCALE)
87
88
89
90
91
92
93
94


%
%
8
6
4
2
0
YEAR 1992
YEAR 1989
3
6
9
12
15
18
21
24
27
30
Unemployment duration (months)



%
%
20
15
10
5
0
INDIVIDUALS NOT RECEIVING BENEFITS
INDIVIDUALS RECEIVING BENEFITS
(95% CONFIDENCE BAND)
3
6
9
12
15
Unemployment duration (months)


%
%
30
25
20
15
10
5
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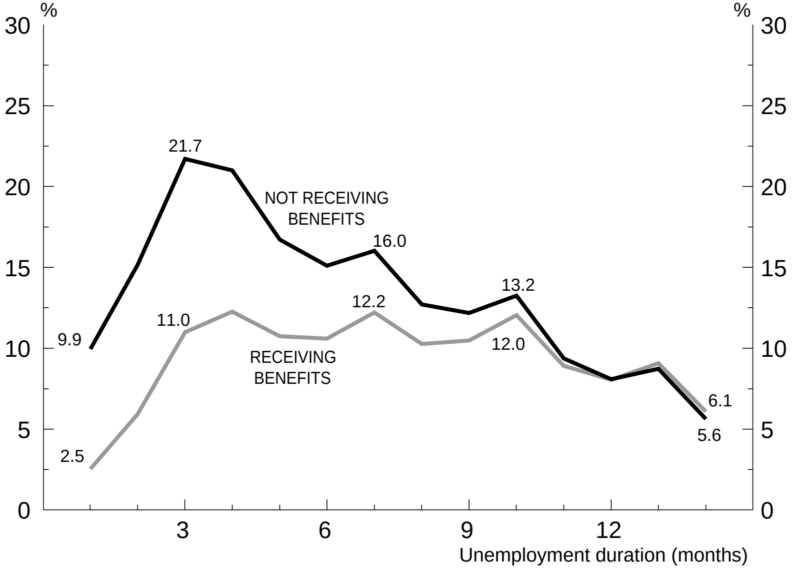
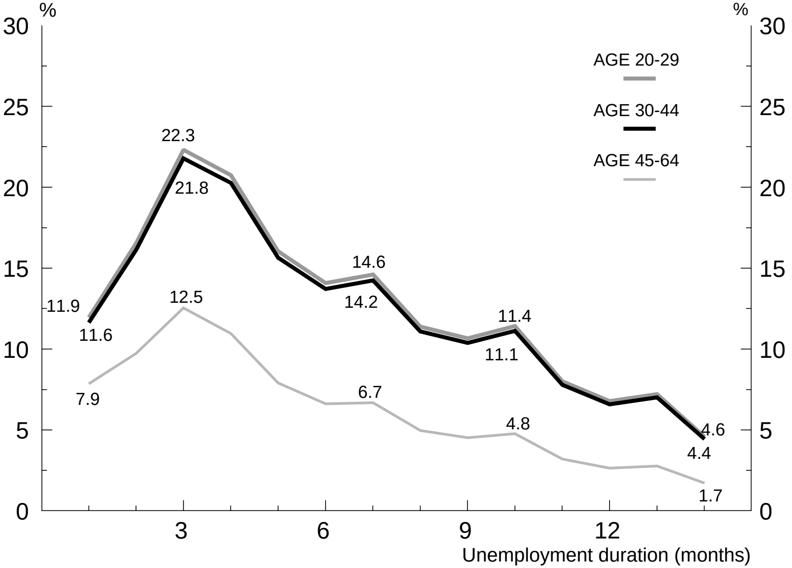
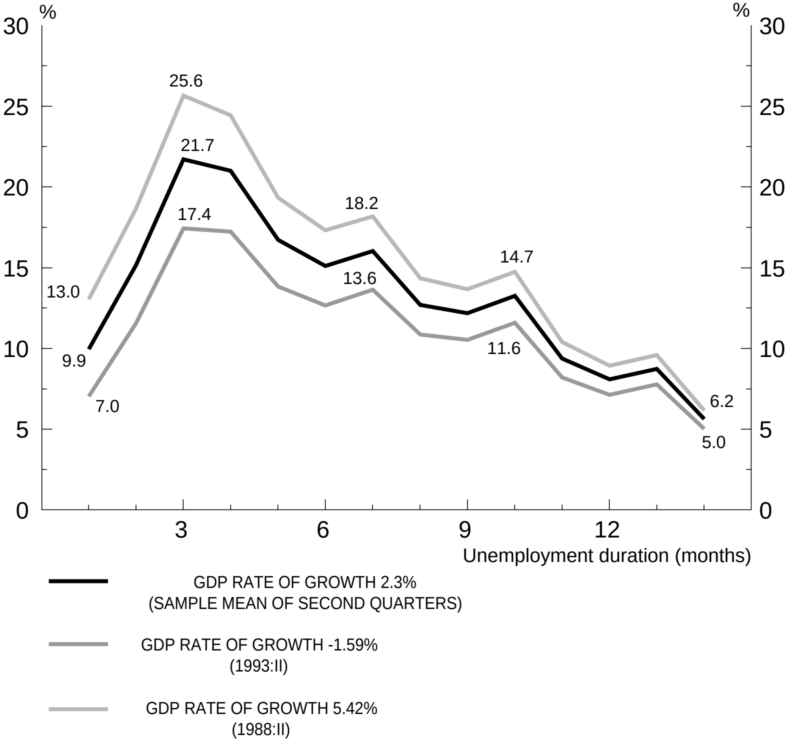
9
12
15
Unemployment duration (months)
INDIVIDUALS NOT
RECEIVING BENEFITS
INDIVIDUALS
RECEIVING BENEFITS


%
30
25
20
15
10
5
0
21.7
NOT RECEIVING
BENEFITS
16.0
13.2
12.2
11.0
9.9
12.0
RECEIVING
BENEFITS
6.1
5.6
2.5
3
6
9
12
Unemployment duration (months)



%
30
25
20
15
10
5
0
AGE 20-29
AGE 30-44
AGE 45-64
22.3
21.8
14.6
14.2
12.5
11.9
11.6
11.4
11.1
7.9
6.7
4.8
4.6
4.4
1.7
3
6
9
12
Unemployment duration (months)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30
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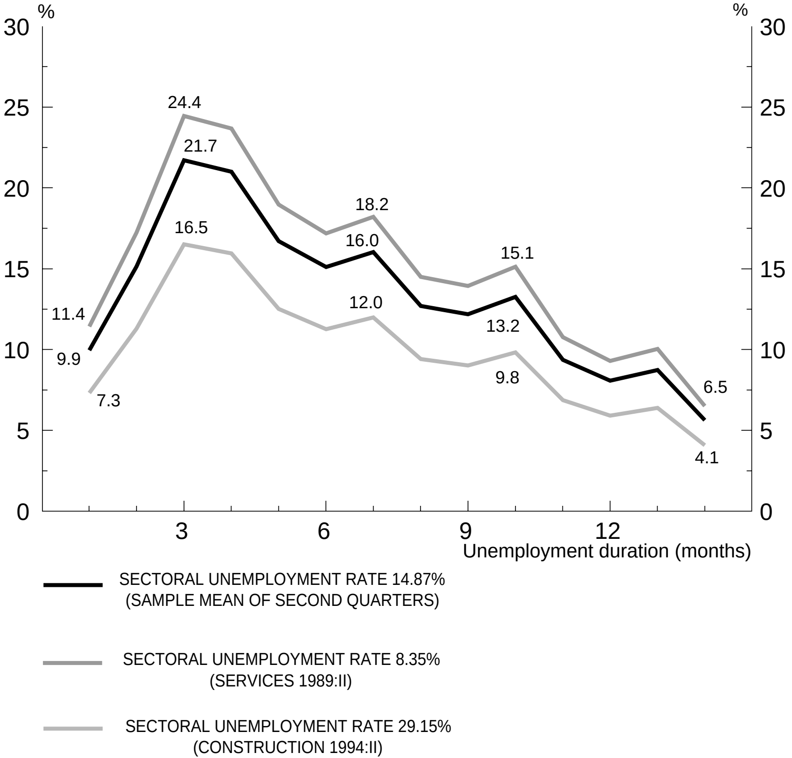
17.4
18.2
13.6
14.7
11.6
13.0
9.9
7.0
6.2
5.0
3
6
9
12
Unemployment duration (months)
GDP RATE OF GROWTH 2.3%
(SAMPLE MEAN OF SECOND QUARTERS)
GDP RATE OF GROWTH -1.59%
(1993:II)
GDP RATE OF GROWTH 5.42%
(1988:II)


%
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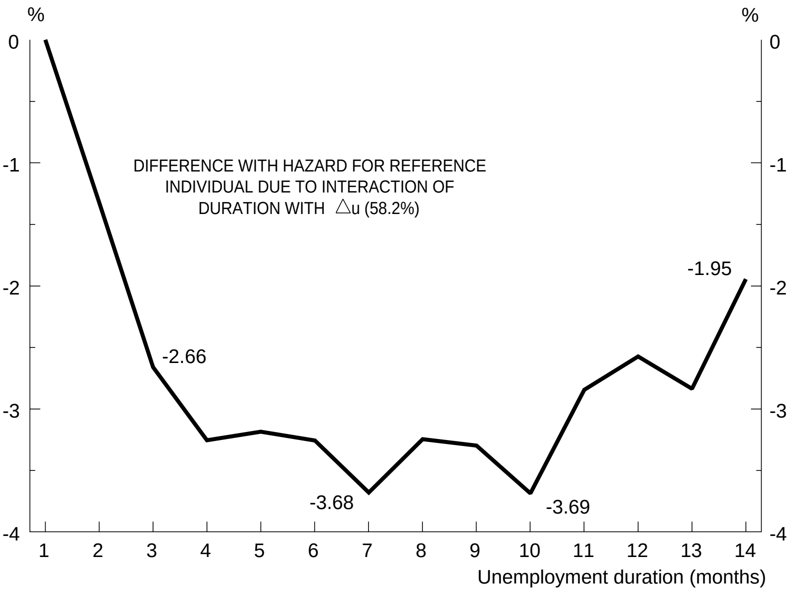
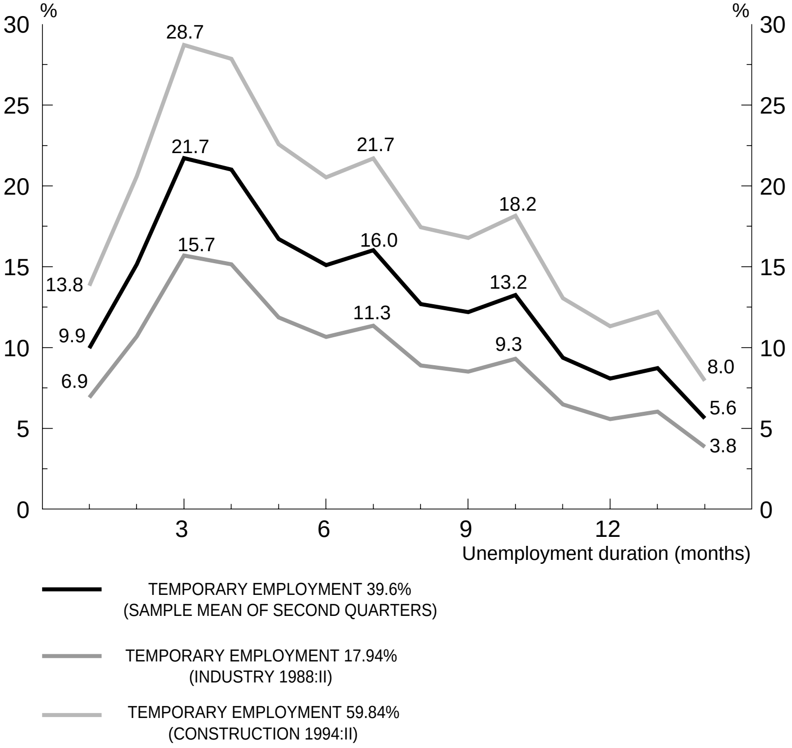
24.4
21.7
16.5
18.2
16.0
15.1
12.0
13.2
11.4
9.9
7.3
9.8
6.5
4.1
3
6
9
12
Unemployment duration (months)
SECTORAL UNEMPLOYMENT RATE 14.87%
(SAMPLE MEAN OF SECOND QUARTERS)
SECTORAL UNEMPLOYMENT RATE 8.35%
(SERVICES 1989:II)
SECTORAL UNEMPLOYMENT RATE 29.15%
(CONSTRUCTION 1994:II)


%
%
0
-1
-2
-3
-4
DIFFERENCE WITH HAZARD FOR REFERENCE
INDIVIDUAL DUE TO INTERACTION OF
DURATION WITH △u (58.2%)
-2.66
-3.68
-3.69
-1.95
1
2
3
4
5
6
7
8
9
10
11
12
13
14
Unemployment duration (months)


%
30
25
20
15
10
5
0
28.7
21.7
21.7
18.2
15.7
16.0
13.8
13.2
11.3
9.9
9.3
6.9
8.0
5.6
3.8
3
6
9
12
Unemployment duration (months)
TEMPORARY EMPLOYMENT 39.6%
(SAMPLE MEAN OF SECOND QUARTERS)
TEMPORARY EMPLOYMENT 17.94%
(INDUSTRY 1988:II)
TEMPORARY EMPLOYMENT 59.84%
(CONSTRUCTION 1994:II)