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Article — Digitized Version

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Vierteljahrshefte zur Wirtschaftsforschung

Provided in Cooperation with:

German Institute for Economic Research (DIW Berlin)

Suggested Citation: Mühleisen, Martin (1994) : State dependence effects in quarterly unemployment histories, Vierteljahrshefte zur Wirtschaftsforschung, ISSN 0340-1707, Duncker & Humblot, Berlin, Vol. 63, Iss. 1/2, pp. 60-68

This Version is available at:

<https://hdl.handle.net/10419/141050>

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Labour Market Dynamics

State Dependence Effects in Quarterly Unemployment Histories

by Martin Muehleisen

Explaining unemployment duration is a major macro-economic puzzle. This paper is concerned with a particular channel through which "hysteresis" or "persistence" effects are likely to enter the labour market. In West Germany, before reunification, Franz (1987) and Pacqué (1990) use human capital arguments to suggest that the duration of unemployment serves as a screening device for employers. Persons who fall into unemployment during a critical period of the business cycle remain there even after the economy has recovered, thus creating a pool of long-term unemployment. This argument rests implicitly on the assumption that wages do not take account of the labour supply of the long term unemployed. The human capital approach is tied to micro economic theory, since the behaviour of both employers who want to fill a vacancy and employees who search for a new job is characterized by the shape of their individual preference structures and the institutional settings in which they operate.

Persistence in aggregate unemployment is postulated to be directly related — via the human capital approach — to effects of state and duration dependence in micro variables, although there is no formal connection between the two concepts. Following Heckman and Borjas (1980), effects of state dependence arise through the influence of

- the current state an individual occupies ("*[Markovian] state dependence*")
- the length of the current spell of unemployment ("*duration dependence*")
- the past history of states, i.e., the cumulated length of unemployment spells before the current spell ("*lagged duration dependence*")

among others, on the probability of the occurrence of future states. Usually, one would expect that the more a person's history is characterized by unemployment, the more likely it is that the person will stay within a current unemployment spell or fall back into unemployment. This is assumed to be

caused by decreasing human capital (deteriorating skills and decreasing motivation) and by stigma effects through which long-term unemployed are discriminated against by employers.

Following job search theory, a popular approach has been to model exit from unemployment into employment (or into non-participation) by duration-type hazard functions (Kiefer 1988) and then to control subsequently for the impact of past unemployment on the hazard rate by means of duration analysis. Duration dependence is easily characterized by an increasing or decreasing hazard function, whereas previous unemployment is captured by the coefficients on appropriate covariates. Unfortunately, it is not quite clear in the literature whether past and current unemployment have an influence on offer arrivals. If we knew this, we could gain information about the rising or falling of the search reservation wage over time from the shape of the hazard function. Most studies, however, have neglected the dynamic structure of the problem completely (see Devine and Kiefer 1991 for a survey).

For example, a recent study by Flaig et al. (1992) finds significant state and duration dependence for German males sampled from the first six waves of the SOEP. They employ a random effects structure, although with a probit specification which can be estimated following a suggestion of Butler and Moffitt (1982). However, they exploit yearly data constructed through point sampling, which is somewhat unsatisfactory since most unemployment spells are not captured by this procedure due to the short average duration of the spells. In Germany, an individual is considered to be "long-term unemployed" after having spent one year in unemployment. Hence, the whole process of becoming long-term unemployed is not observed using a period of one year for analysis.

The next section will deal with an introduction of the applied statistical model which is well known from the seminal paper of Heckman (1981a). Issues of unobserved heterogeneity and its relation to spurious state dependence are discussed together with the problem of initial conditions. We then introduce the data set. It will be argued that quarterly data are best for the problem at hand. Next, the concept of estimation by simulated maximum likelihood will

be introduced, and it will be shown how the various issues of the statistical model can be incorporated by the estimation procedure. Finally come the discussion and conclusion.

Statistical Model:

Repeated Choice Between Discrete Alternatives

Let the employment process on the labour market be characterized by the following reduced form probability model for a given period t . Denote by w the maximum wage offer a worker receives in t . Assuming that a worker i accepts an offer if and only if w is higher than her reservation wage w^* , we can write the probability of a worker having a job as:

$$\begin{aligned} \text{Prob} ("i \text{ receives maximum offer } w \text{ and enters a job"}) \\ &= \text{Prob} ("i \text{ enters a job"} \mid w > w^*) \cdot \text{Prob} ("i \text{ receives } w > w^*") \\ &= \text{Prob} ("i \text{ receives } w > w^*"). \end{aligned}$$

Usually, the probability of entering a job is split up into a probability of receiving an offer at all and the conditional probability of accepting that offer (see, for example, Winter-Ebmer 1991). Since no data on job offers are available, the issue here is how to specify the distribution of wage offers within a period. Assuming there is at least one offer per period, we approximate the distribution of the maximum of the wage offers by $w_{it} \sim N(\mu_{1t}(x_{it}, h_{it}), \sigma_{1t}^2)$ where x_{it} and h_{it} represent vectors of exogenous variables and the worker's unemployment history relevant to the mean of the distribution, respectively. The reservation wage shall be characterized by another normal distribution which we write as $w_{it}^* \sim N(\mu_{2t}(x_{it}, h_{it}), \sigma_{2t}^2)$, conditioned on the same set of variables and history¹. Hence, the probability of a worker being unemployed is equal to $\text{Prob}(w - w^* < 0 \mid x_{it}, h_{it})$ with the difference of the wage terms distributed normally. Observing decision outcomes for periods $t = 1, \dots, T$, we then receive the following model for the unemployment process. Let the latent variable y_{it}^* be defined as $y_{it}^* = w_{it} - w_{it}^*$, i.e., the difference between offered wage and reservation wage for worker i in period t . Then we have: $y_i \sim N(\mu(x_i, h_i), \Omega)$ with $y_i = (y_{i1} \dots y_{iT})'$, x_i and h_i defined accordingly, and it holds that:

Worker i is unemployed at $t \Leftrightarrow y_{it}^* < 0$.

Let an indicator dummy variable be defined as $d_{it} = 1$ iff $y_{it}^* < 0$, and $d_{it} = 0$ otherwise, then a sequence of an individual's observed decisions can be written as a vector of indicators: $d_i = (d_{i1} \dots d_{iT})'$. From individual histories, we can construct a likelihood-function by multiplying over all workers the probabilities for the states the workers occupy at every period. Let l_i be the likelihood for the complete history which we observe for worker i . Introducing a vector Θ which is assumed to contain all relevant parameters, it holds:

$$l_i(\Theta; x_i, h_i) = \text{Prob}(d_i \mid \Theta; x_i, h_i)$$

which means the likelihood contribution of individual i is the value of a multi-dimensional normal probability, given Θ .

That probability cannot be simplified to a product of one-dimensional probability integrals, since an explicit assumption on the covariance matrix Ω has not been made. Adding up the logarithms, the log-likelihood function is obtained and will be maximized over Θ .

It is assumed that data for I individuals over T periods is available. We shall be concerned with the following model (cf. Heckman 1981a): $y_{it}^* = \mu y_{it}^* + \epsilon_{it}$ and μ_{it}^* is given by

$$\mu y_{it}^* = x_{it}' \gamma + \sum_{j=1}^{J_1} \gamma_j d_{i,t-j} + \sum_{j=1}^{J_2} \lambda_j \prod_{l=1}^j d_{i,t-l} + \gamma_0 \left[\sum_{j=1}^{\infty} d_{i,t-j} - \sum_{j=1}^{\infty} \prod_{l=1}^j d_{i,t-l} \right] \quad (1)$$

and $\epsilon_{it} \sim N(0, \Omega)$. The first term on the right hand side captures the influence of variables which are assumed to be exogenous for the process. Variables in x_i may or may not vary over time, although their impact upon y_i^* is assumed to be constant over time. The rest of the right hand side separates component-wise the impact of h_{it} , the past history of unemployment: The second term reflects single decisions of the individual back over some fixed time length J_1 . For simplicity, this influence is also assumed to be time-invariant, so that the γ -parameters collapse to γ_j , resulting in a time-homogeneous J_1 th-order Markov process. The third expression represents the cumulative effect of past choices over an interval with length J_2 . Assume that $d_{i,t,j} = 0$ for some j' and $d_{i,t,k} = 1$ for all $k < j'$. Hence, the product in the third term will be positive only for $j < j'$ and zero elsewhere. Therefore, λ can only be identified if there is at least one non-interrupted spell of choices of length j for which d_{it} is positive. The fourth term simply represents the sum over the complete decision path minus the length of the current spell of positive indicators. In contrast to the suggestion of Heckman (1981a), this paper will not be concerned with habit persistence which would lead to the inclusion of a lag structure for y_{it}^* in the equation.

This econometric specification will be utilized for the analysis of unemployment histories in a rather simple fashion. Following Heckman and Borjas (1980), we now identify the different types of state dependence in specification (1). Initially, a Markovian type of state dependence enters through the second term. Obviously, it matters a great deal for the wage offer distribution whether the worker is in a state of employment or not at time $t-1$. In order to capture effects of depreciating human capital during the first periods after workers have fallen into unemployment, further lagged choice terms may be included. Second, the impact of the length of the current unemployment spell is called duration dependence and is captured by the λ -parameters. They contribute to μ_{it} only if the respective product is positive which requires that e.g. for λ_j the actual spell of unemployment has at least length j .

Third, the difference in brackets measures lagged duration dependence since, if we subtract the length of the cur-

¹ Note that benefits and wages can also be written as a function of individual characteristics and unemployment history. To avoid problems arising from simultaneous equations, we shall leave them out in the sequel.

rent spell of unemployment from the total length spent in unemployment, we end up with the length of previous spells of unemployment. The summation over an infinite length is merely a notational nuisance, since what matters is the difference which is measured from the time of entrance to the labour market. For reasons of data shortage which shall be discussed later, we restricted lagged duration going back at most to 1974. The interpretation is obvious: total time of unemployment in the past is a measure for missing on-the-job experience as well as a signal for the employer that the productivity of the worker is possibly low. This should lead directly to a shift in the wage offer distribution. Note, however, that this variable is correlated with age.

Turning to some methodological problems encountered by estimating this type of model, one first has to mention the problem of unobserved heterogeneity which could result in spurious state dependence (Heckman 1981c). In order to take account of this, the error term ϵ_{it} is decomposed into $\epsilon_{it} = \alpha_i + v_{it}$ with the following interpretation: the α_i are assumed to be drawn once for an individual from a distribution $N(0, \sigma_\alpha^2)$ and then remain constant over all periods. Thus, we can think of the random effects α_i as representing unobserved heterogeneity. Assuming v_{it} *i.i.d.* $N(0,1)$ across time and individuals we receive a typical random effects covariance structure:

$$\Omega_{RE} = I + \sigma_\alpha^2 \mathbf{1}\mathbf{1}' \quad (2)$$

with $\mathbf{1}$ as a vector of T ones and I the $T \times T$ identity matrix. A model with this covariance matrix can be estimated following Butler and Moffitt (1982). However, the random effects model is usually not the most powerful model for explaining persistent individual behaviour because it seems a strong assumption to keep individual heterogeneity constant over time (Heckman 1981c). Thus, we increase the flexibility of this approach by allowing v to have an autoregressive structure of the kind

$$ny_{it} = \rho ny_{i,t-1} + \xi_{it} \quad (3)$$

with ξ_{it} *i.i.d.* $N(0,1)$. A condition for stability is that $|\rho| < 1$. This adds typical elements $\sigma_{\rho s} \equiv \rho^{1-r-s} / (1-\rho^2)$ to the covariance matrix. Further possible covariance structures — which are not applied here — include individual heterogeneity varying over time which results in one- and more factor models (Heckman 1981a). Nonetheless, testing between unobserved heterogeneity and true state dependence has now become a matter of testing the significance of the parameters σ_α^2 and ρ , respectively.

The second major obstacle for properly estimating a dynamic process lies in the specification of the initial conditions by which the process is driven. Heckman (1981b) gives two examples how this problem is typically excluded, i.e., how it is justified that decisions which have been made before sampling are treated like exogenous factors. First, assuming that the presample history of the process is completely exogenous to the observed process implies that the latter has either just begun or that the error terms are

serially independent. Second, assuming that the process is initially stationary means that there exists an equilibrium at the outset — a hypothesis which is generally difficult to maintain. Both concepts are rather unsatisfactory although they could not be avoided in most cases. There is, however, a third approach suggested by Heckman (1981b) which has proven to work well, at least for the kind of Monte-Carlo analysis presented in his paper. The idea is to approximate the initial state of a process by a probit specification

$$y_{i0}^* = x_{i0}'\beta_0 + \epsilon_{i0} \quad (4)$$

where d_{i0} is an indicator for the sign of y_{i0}^* . The vector of exogenous variables at the initial state, x_{i0} , should consist of a subset of the variables which are contained in the x_{it} . The disturbance term ϵ_{i0} is assumed to be distributed standard normally and allowed to be freely correlated with ϵ_{it} , $t = 1, \dots, T$. Hence, this procedure amounts to enlarging the original model on y_{it}^* with a probit model for y_{i0}^* . The joint distribution of $\{y_{i0}^*, y_{i1}^*, \dots, y_{iT}^*\}'$ has the mean $(x_{i0}'\beta_0 \quad my_{i1} \dots my_{iT})'$ and a covariance matrix which can be obtained by augmenting Ω with the vector of covariances $(\sigma_{01} \dots \sigma_{0T})'$. Then, however, the maximization of the respective likelihood function has to be carried out over the also enlarged parameter vector

$$(\Theta' \beta_0' \sigma_{01} \dots \sigma_{0T})'$$

This also illustrates the limitations of this approach. As we shall see, we have to economize on the number of parameters of the model and hence, if T is large one must estimate a large number of additional parameters which might conflict with the computational performance of our estimation. Note also that we only specify initial conditions for $j = 0$ but that there are many more presampling periods involved in equation (1). In principle, one could include more probit models for past periods $y_{i,j}^*$, $j = 1, 2, \dots$, but this does not seem to be a very useful approach.

Data

The data for our estimations are taken from the calendar data of the first six waves of the Socio-Economic Panel (SOEP) for West Germany, covering the years 1984 to 1989. Since the unemployment process will be analysed with a discrete approach, one must decide on the sampling period very carefully, as there is no evidence on the length of a period within which an unemployed individual makes her decision to accept an offer or not. In this paper, we set the base periods equal to the four quarters of a year in that we consider individuals as unemployed if they report unemployment in at least one single month of the respective quarter. We did that for four reasons:

First, a calendar quarter of a year seems to be a reasonable time span to collect and compare offers from various firms. Many firms may have a higher fluctuation near the end of a quarter, so that applicants might have to wait for one or two months until they could enter a new job. Looking at macro fluctuations, one can project cyclical ups

and downs by using quarterly data on aggregate output or unemployment. Second, about 40 percent of all unemployment spells have a duration between one and three months. If one chooses a larger time span for the period of analysis it would be difficult to establish a definition when an individual should be considered unemployed in a particular period. A large number of short spells are likely to be dropped because they might be preceded and succeeded by long spells of employment.

Third, the average duration for uncensored spells is 6.54 months. This implies that one must allow for the problem that state dependence could be overestimated because an average spell overlaps sampling periods (Narendranathan and Elias 1990). If we chose a shorter sampling period, this problem increases significantly. Fourth, shorter sampling periods would also result in a very high computational effort. Since individuals will be followed over several years, the total number of periods in our model would increase rapidly. As soon will be evident, estimations might then become intractable.

We chose $T = 13$ quarters for the length of our panel data set (1984.I to 1987.I). We want to capture a time interval of three years for our analysis, long enough to investigate long-term unemployment and short enough to be computationally feasible². We also compromise on the bias resulting from panel attrition, which gets relatively higher the more panel waves are involved. Allowing for up to four pre-sample periods, we have to collect data for 17 periods from the first four waves. We obtain a sample of 8864 persons who responded during all four of these waves.

Problems of modelling decisions between taking jobs and non-participation or self-employment are to be avoided. Some individuals take care of children, retire, or stay in school and are thus unable to become subject to an unemployment process. Hence, we restrict the sample only to individuals of medium age and, moreover, only to men because the behaviour of women is more markedly characterized by states of non-participation. Public servants are supposed to be continuously employed and thus do not contribute to the variation in the dependent variable. Thus, we derive subsample of 1211 males aged between 19 (in 1984) and 57 (in 1987) who report neither self-employment nor being in school or acting as civil servants in any of the years. Individuals with missing values in any variable have also been deleted. This subsample has been split up into two groups: group A consists of 190 persons who have experienced at least one spell of unemployment between quarters 1983.I and 1987.I. Group B is the complement of A. In order to compromise on computational cost, we restricted the sample size for the estimation to 400 individuals. Therefore, a choice-based data set is constructed by selecting an exhaustive sample of group A and a random sample of 210 individuals from group B.

The transitions into and out of unemployment for group A are given in Table 1. On average, in every period only about 13 per cent of the members of this group change their labour market status.

² Note that 13 periods are required in order to estimate transition probabilities three times for every calendar quarter. Thereby, seasonal idiosyncrasies are captured evenly.

Table 1

Labour Market Transitions for Group A

| d_{it} | 1984 | | | | 1985 | | | | 1986 | | | | 1987 |
|--|------|------|-----|-----|------|-----|-----|-----|------|-----|-----|-----|------|
| Distribution of unemployment | | | | | | | | | | | | | |
| 0 | 116 | 131 | 138 | 134 | 127 | 134 | 133 | 136 | 126 | 139 | 139 | 137 | 135 |
| 1 | 74 | 59 | 52 | 56 | 63 | 56 | 57 | 54 | 64 | 51 | 51 | 53 | 55 |
| Long-term unemployed (at least four quarters) | | | | | | | | | | | | | |
| | 35 | 34 | 31 | 26 | 29 | 29 | 32 | 30 | 26 | 25 | 30 | 33 | 35 |
| Transitions | | | | | | | | | | | | | |
| 0 to 1: | 8 | 12 | 15 | 15 | 8 | 13 | 14 | 18 | 4 | 10 | 6 | 16 | |
| 1 to 0: | 23 | 19 | 11 | 8 | 15 | 12 | 17 | 8 | 17 | 10 | 4 | 14 | |
| Transitions (percent) | | | | | | | | | | | | | |
| 0 to 1: | 4.2 | 6.3 | 7.9 | 7.9 | 4.2 | 6.8 | 7.4 | 9.5 | 2.1 | 5.3 | 3.2 | 8.4 | |
| 1 to 0: | 12.1 | 10.0 | 5.8 | 4.2 | 7.9 | 6.3 | 8.9 | 4.2 | 8.9 | 5.3 | 2.1 | 7.4 | |

The most significant difference between groups A and B lies in lagged unemployment duration with means 2.12 for A and 0.23 for B, already indicating a possibly strong lagged duration dependence. Further, more members of group A seem to live alone, belong to the blue-collar group and have less children in younger though more in older age. Note that we also have an over representation of foreigners in our sample which is a result of the particular sampling features of the SOEP. Employing aggregate macro data as tension indicators has been pursued here by including the seasonally un-adjusted male unemployment rate for West Germany. It captures not only labour market tension in

general but also seasonal effects which the German labour market is strongly subject to.

Results

The following tables show coefficients of the several estimated models and their asymptotic t-values in every column. The following restrictions have been imposed: First of all, we let $J_1 = J_2 = 4$ which reflects that we allowed for four pre-sample periods in our data extraction. As mentioned in the data section, we also decided to restrict λ_1, λ_2 and λ_3 to zero and allow for the effect of current duration of unemployment only through the indicator for long-term

Table 2

Estimation of Dynamic Specifications of γ_{it}^* with Autoregressive Residuals and Random Effects¹⁾

| Variable | Model: | [A] | | [B] | | [C] | |
|--|-------------------|---------|--------|---------|--------|---------|--------|
| | | | | | | | |
| Constant | | 2.7203 | 3.68 | 2.7289 | 4.56 | 2.7187 | 4.37 |
| Age | (/ 30) | 1.1775 | 1.02 | 0.8128 | 0.88 | 1.2340 | 1.32 |
| Age squared | (/ 1000) | -0.4913 | -1.01 | -0.3695 | -0.93 | -0.5496 | -1.37 |
| Nationality | (1 = Foreign) | 0.0045 | 0.04 | 0.0147 | 0.15 | -0.0234 | -0.24 |
| Disability | (1 = yes) | -0.2794 | -2.30 | -0.2047 | -2.01 | -0.2242 | -2.13 |
| Number of Children | (with age 0- 6) | 0.0365 | 0.41 | 0.0297 | 0.36 | 0.0420 | 0.50 |
| | (with age 7-10) | -0.1302 | -1.67 | -0.0998 | -1.46 | -0.1125 | -1.55 |
| | (with age 11-15) | -0.1579 | -2.15 | -0.1389 | -2.01 | -0.1341 | -1.83 |
| Partnership | (1 = yes) | 0.1864 | 1.50 | 0.0892 | 0.85 | 0.0702 | 0.65 |
| State | (1 = North/West) | -0.3361 | -3.23 | -0.2560 | -2.90 | -0.2430 | -2.59 |
| Region | (1 = Rural) | -0.0670 | -0.67 | -0.0591 | -0.70 | -0.0573 | -0.65 |
| Years of Schooling | (/ 10) | 0.2890 | 1.22 | 0.2176 | 1.07 | 0.1616 | 0.76 |
| Job Status | (1 = Blue Collar) | -0.3757 | -3.47 | -0.2710 | -2.76 | -0.2268 | -2.33 |
| Union Membership | (1 = yes) | 0.1835 | 1.95 | 0.1229 | 1.51 | 0.0869 | 1.11 |
| $d_{i,t-1}$ | | -2.6662 | -35.16 | -2.5792 | -14.98 | -2.4432 | -13.56 |
| $d_{i,t-2}$ | | | | 0.0319 | 0.23 | 0.0507 | 0.38 |
| $d_{i,t-3}$ | | | | -0.3248 | -3.39 | -0.2325 | -2.30 |
| $d_{i,t-4}$ | | | | -0.7850 | -6.99 | -0.4694 | -3.79 |
| $\prod_{j=1}^4 d_{i,t-j}$ (long-term ue.) | | | | 0.3634 | 2.31 | -0.0533 | -0.32 |
| Lagged ue. duration | | | | | | -0.0660 | -5.79 |
| Male ue. rate (/ 10) | | -1.0693 | -3.99 | -0.8605 | -3.04 | -0.9802 | -3.36 |
| σ_α^2 | | 0.2198 | 3.41 | 0.0011 | 0.03 | 0.0155 | 0.40 |
| σ_e | | -0.0370 | -0.82 | 0.0475 | 0.61 | 0.0898 | 0.99 |
| Log Likelihood | | 407.95 | | 392.06 | | 383.93 | |
| AIC ²⁾ | | 0.7035 | | 0.6838 | | 0.6721 | |
| Pseudo R ² (Aldrich/Nelson) ³⁾ | | 0.67 | | 0.83 | | 0.80 | |
| Pseudo R ² (Veall/Zimmermann) | | 0.84 | | 0.95 | | 0.94 | |

1) Columns contain estimates and asymptotic t-values. Observations have been weighted due to choice-based sampling. Negative coefficients indicate increasing risk of unemployment (see definition of γ_{it}^*). — 2) AIC is Akaike's Information Criterion defined as $AIC = 2/n * (-L(\hat{\theta}) + p)$ where p is the number of estimated parameters and n is equal to sample size ($n = 1211$). — 3) Pseudo-R² measures are derived from the log-likelihood values at the estimated parameter values and at $\beta = 0$ (except for the constant). Veall and Zimmermann (1990) proposed a corrected version of the pseudo-R² by Aldrich/Nelson which takes values in the full range of the unit interval.

unemployment. Further, the history of individuals has been included stepwise, namely by estimating a specification with past employment status only (A), plus a set of lagged dummies and a duration term (B), and by finally including lagged unemployment duration (C).

We shall first discuss the results concerning the dynamic structure of the unemployment process and, second, turn to the coefficients of the covariates. Table 2 gives the results of the simple multi-period probit estimation with initial conditions correction. The first lag of the indicator obviously has a great impact on the estimation results since employment relationships in general are characterized by a high degree of stability, apart from all considerations of unemployment dynamics. Since we have more than 80 per cent of our sample with no fluctuations in employment status at all, the high significance of $d_{i,t-1}$ is no surprise because the lagged status predicts the current status very well. A negative value for ρ in specification [A], however, indicates the need for further dynamic variables because there seems to be no useful explanation of why unobserved idiosyncratic characteristics should change the other way round every period. Looking at specifications [B] and [C] which allow for dynamics up to one year ago, we find a striking difference between the estimates for long-term unemployment which are positive and with large t-values in [B] and negative, though close to zero, in [C]. An interpretation that would relate rising employment chances positively with long-term unemployment as suggested by [B] would be short-sighted because of identification problems: if we add the coefficients of $d_{i,t-4}$ and of long-term unemployment in [B] and [C], we receive values which are not very different for both equations. Since long-term unemployment shows the expected sign in [C], lagged unemployment duration, which is only contained in [C], seems to represent unobserved characteristics which govern the labour market performance of individuals because, if it is not included, the coefficient of long-term unemployment cannot be estimated properly.

Long-term unemployment can not be regarded as indicator for personal heterogeneity; it seems to capture rather weakly human capital decay and demotivation processes which set in after having spent several months in unemployment. The significance of lagged unemployment duration is interpreted as follows: taking into account that average lagged unemployment duration differs widely between groups A and B, this variable seems to capture a large amount of previously unobserved workers' heterogeneity that otherwise had to be controlled for by appropriate covariance measures. Among others, personal appearance, attention and motivation, but also misfortune on the labour market, may be comprised in this labour market performance indicator. Note however that previous unemployment is, in principle, endogenous and that it is correlated with age. Therefore, we have to regard lagged unemployment duration rather as a proxy for a subset of individual factors which we cannot observe in our panel.

In Table 3, we present results obtained after we allowed for initial conditions using the Heckman (1981b) approach. Because of the computational burden, we dropped the observations of the last four periods, thus setting $T = 9$. The sample selection is different because due to lower panel attrition, we received a higher number of people with unemployment spells (225 individuals). Therefore the weights were recalculated but all other features remain the same, including the sample size of 400. The results did not change significantly compared with Table 2; only the negative result for ρ finally disappeared, confirming our suggestion that there is a large amount of unexplained heterogeneity in the model, part of which is captured by lagged unemployment duration (contained in the probit model for $t = 0$). This is also confirmed by the considerably lower value we obtained for σ_α^2 compared with [A] and by the amount of correlation found between the initial and later periods. Lagged unemployment duration might not be an ideal variable in the initial probit specification since it is, in principle, endogenous but leaving it out would result in a very poor initial probit performance and hence in a badly suited basis for estimating the intertemporal correlation coefficients (see also Flaig et al. 1992 on this topic).

Summing up, we claim that the specification for my^*_{it} estimated in [C] serves as a useful description of the unemployment process. Unobserved heterogeneity is controlled for to a comparably large extent by the covariance structure and by including lagged unemployment duration which yields, on the one hand, unbiased parameter estimates for the covariates but, on the other hand, is still somehow unsatisfactory, since we have no possibility of getting a deeper look into which factors have ultimately been responsible for the labour market performance of individuals.

Turning to the covariates, first of all strongly negative coefficients on the labour market tension indicator (aggregate unemployment) and federal state are found, less on the rural region dummy. These variables represent cyclical and seasonal effects as well as the regional distribution of unemployment and can therefore be regarded mainly as demand side variables. The local division into only two areas, north/west vs. south, is certainly not totally convincing, but splitting up the sample using federal state dummies would have been computationally forbidding. A general upswing in the economy has a direct effect on the (re-)employment chances of individuals, which is not surprising at all.

On the other hand, the labour supply characteristics such as years of schooling and the dummies on blue-collar job and union membership are not as significant as the demand side factors. Although one's job status makes a great difference education does not influence employment probabilities very much. People with more education have a lower probability of falling into unemployment but lose their comparative advantage while being unemployed.

Table 3

Estimation of Dynamic Specifications (allowing for initial conditions)¹⁾

| Variable | [A, T = 9] | | | |
|---|------------|--------|--|---------------|
| Model coefficients | | | Initial Conditions | |
| Constant | 2.7963 | 3.35 | Constant | 0.2199 0.35 |
| Age | 0.2266 | 0.18 | Age | 0.6925 2.95 |
| Age squared | -0.1012 | -0.18 | Disability | -0.0025 -0.01 |
| Nationality | 0.0432 | 0.40 | State | -0.0964 -0.52 |
| Disability | -0.2873 | -2.06 | Schooling | 0.6945 1.73 |
| Number of (age 0-6) | 0.1216 | 1.45 | Unemployment duration 74-82 | -0.7665 -4.41 |
| Children (age 7-10) | -0.0599 | -0.79 | Correlations with ϵ_0 | |
| (age 11-15) | -0.1957 | -2.86 | σ_{01} | 0.0744 0.53 |
| Partnership | 0.2232 | 1.82 | σ_{02} | 0.1873 1.61 |
| State | -0.2318 | -2.21 | σ_{03} | 0.2003 1.39 |
| Region | -0.0212 | -0.24 | σ_{04} | 0.2762 2.07 |
| Years of Schooling | 0.4179 | 1.68 | σ_{05} | 0.3210 2.68 |
| Job Status | -0.2557 | -2.30 | σ_{06} | 0.2937 1.63 |
| Union Membership | 0.1392 | 1.69 | σ_{07} | 0.4423 4.00 |
| $d_{i,t-1}$ | -2.6084 | -21.80 | σ_{08} | 0.3506 3.41 |
| Male unemployment rate | -1.0902 | -2.81 | σ_{09} | 0.2537 1.97 |
| σ_α^2 | 0.0894 | 1.34 | | |
| e | 0.0050 | 0.08 | | |
| Log Likelihood | 377.13 | | | |
| AIC ²⁾ | 0.6773 | | | |
| Pseudo R ² (A/N) ³⁾ | 0.82 | | | |
| Pseudo R ² (V/Z) | 0.95 | | | |

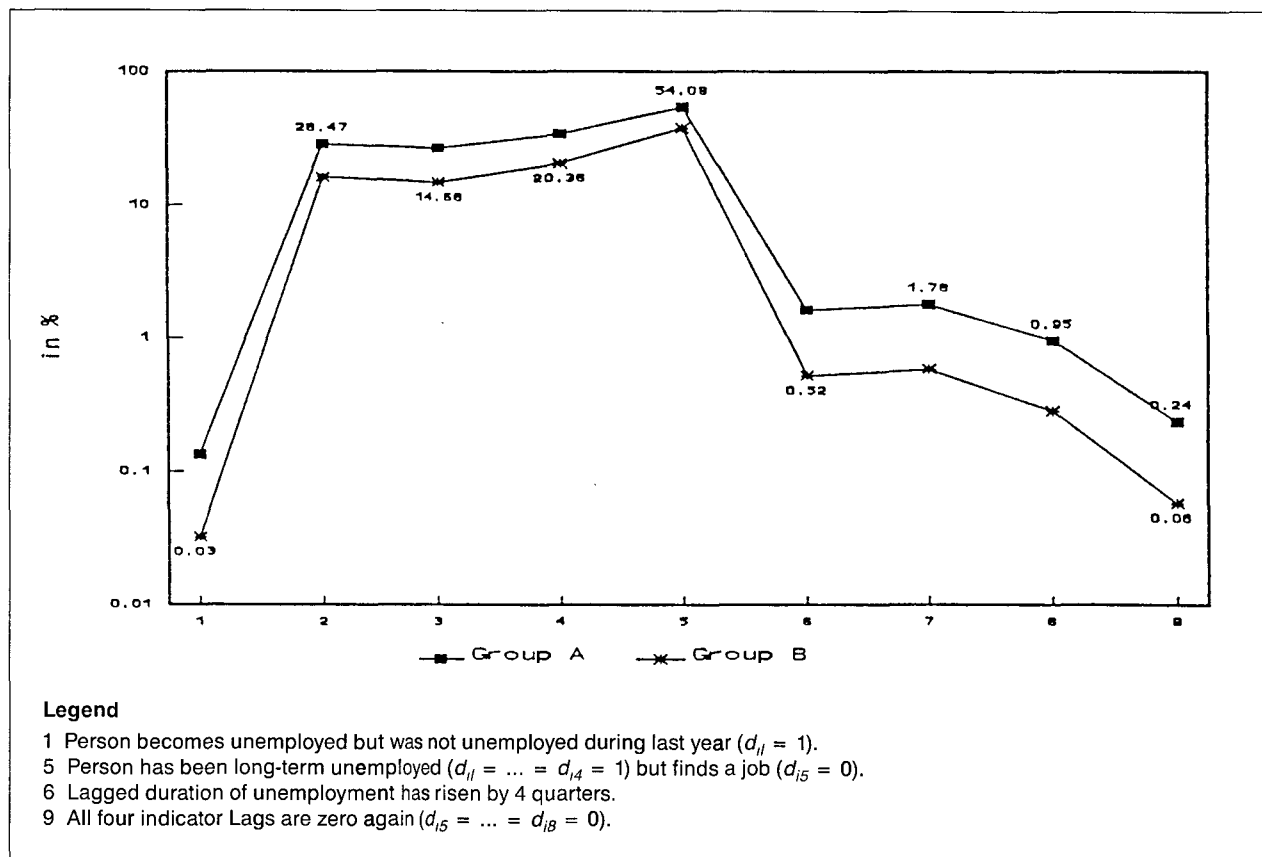
1) Columns contain estimates and asymptotic t-values. Observations have been weighted due to choice-based sampling. Negative coefficients indicate increasing risk of unemployment (see definition of y_{it}^*). — 2) AIC is Akaike's Information Criterion defined as $AIC = 2/n * (-L(\theta) + P)$ where P is the number of estimated parameters and n is equal to sample size ($n = 1211$). — 3) Pseudo-R² measures are derived from the log-likelihood values at the estimated parameter values and at $\beta = 0$ (except for the constant). Veall and Zimmermann (1990) proposed a corrected version of the pseudo-R² by Aldrich/Nelson which takes values in the full range of the unit interval.

Personal characteristics like age, nationality, partnership and children do not contribute much to the explanation of unemployment, except for disability, which has a strongly negative coefficient throughout. We note, however, that the coefficients have the expected signs. The estimates themselves are fairly robust since the various specifications did not lead to much change, in coefficients or in asymptotic t-values.

We used the coefficients of equation [C] in Table 2 for an analysis of the change of the probabilities of being in the status "unemployment" during a spell of unemployment, separated by group A and B. In Figure 1, we plotted $Prob(d_{it} = 1)$ for 9 consecutive periods (decisions are assumed to be taken at the beginning of every period). The unemployment spell is supposed to start in 1 and end in period 5. For

the covariates of both representative individuals we used average values. The aggregate unemployment rate has been constantly set to 8 percent. At the beginning of period 1, both individuals have a low risk of becoming unemployed (0.13% for group A vs. 0.03% for B). As soon as they have fallen into unemployment, the chances of getting a job again differ dramatically. Person A has a chance of 28% to remain unemployed at $t = 2$ and of 54% at $t = 5$ (when she becomes long-term unemployed). Person B has only a 38% probability of remaining in long-term unemployment. Since the two individuals differ most significantly in the time they have spent in previous unemployment spells, this is another sign that lagged duration of unemployment is largely responsible for different labour market performance of individuals.

Unemployment probabilities $\text{Prob}(d_{it} = 1)$ at beginning of periods for representative members of groups A and B during an assumed yearly spell of unemployment (logarithmic scale).



In principle, we could have looked at the development of employment probabilities after more than four quarters of unemployment, but since we do not have more than four lagged indicators in our model, this would only be driven by the quarterly increase of age. It is more interesting to let the individuals get a job again, which happens at the beginning of period 5. The chances of becoming unemployed again in the next period fall immediately. They are not as high as in period 1 because there are still the negative effects of lagged unemployment indicators, and, of course, lagged duration of unemployment rises the very moment the persons entered their new jobs. The influence of the lagged indicators decreases and in period 9, the unemployment odds are 0.24% for A and 0.06% for B, which is small, as in period 1, although we note that the values have doubled compared to then. This shows how past unemployment spells influence current labour market chances: although unemployment has been successfully overcome by a person, its mere occurrence dramatically increases future odds of falling into unemployment.

Conclusion

After controlling for a number of biasing effects such as unobserved heterogeneity and initial conditions, we still find a high degree of state dependence in the process. Besides a strong influence of the current state individuals occupy (which is rather trivial), lagged unemployment duration plays a significant role for the performance of individuals on the labour market. We also find that, after having spent between 6 to 9 months in unemployment, the chances of a person leaving unemployment significantly drop. After a spell of unemployment, the probability of becoming unemployed again rises significantly. Without giving evidence on the degree to which persistence or hysteresis prevails in the economy, this certainly confirms the argument that unemployment always has a tendency to sustain itself because of the ensuing human capital decay.

Active employment policies have a direct effect on future labour market performance because they leave people with a history which is less tainted by unemployment.

Therefore, they act against the state dependence effects which are responsible for the hysteresis or persistence effect identified in this paper. However, these measures have no influence on observable (age, health) or unobservable personal characteristics (motivation, appearance). They may also serve as a signal employers in the same way as spells of unemployment in the past or present do. However, active employment policy seems to be most beneficial if it is

applied to young people who are on the point of entering the labour market. If they can be kept employed in the beginning, then the process of human capital decay will either not set in at all, or will start from a much higher level. On the other hand, employment measures might also be efficient if they are applied directly after the shock of a first layoff, in order to prevent these people from accumulating unemployment histories.

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