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Testing for State Dependence Effects in a Dynamic Model of Male Unemployment Behaviour

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Abstract: A dynamic random effects probit model is estimated on the first six waves of the German Socio-Economic Panel to test for state dependence effects in male unemployment behaviour. Estimation of the model is based on the marginal likelihood approach. In the model an individual's unemployment probability at a given point in time within the period 1985 - 1989 depends on his labour force status in the previous period and on the cumulated duration of past unemployment. Controlling for observed and unobserved population heterogeneity, we show that there are strong state dependence effects in individual unemployment dynamics with respect to both the incidence and the duration of an individual's past unemployment. These results are compatible with the 'scar theory' of unemployment which holds that an individual's previous unemployment experience may have long-term effects because it induces a depreciation of human capital and/or acts as a screening device in employers hiring decisions.

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1. Introduction

The persistence of long-term unemployment in most OECD economies has raised the question whether a causal relationship exists between an individual's unemployment experience and his or her future employment prospects. Most researchers have taken such a relationship, termed 'true' or 'structural' state dependence in the literature (Heckman / Borjas 1980; Heckman 1981a), for granted. It is explained by the hypothesis that unemployment, especially if it has been long-term, impairs an individual's future employment prospects because it leads to a depreciation of human capital or acts as a negative signal for firms screening job applicants. Given that such a relationship exists profound implications for both unemployment theory and labour market policy arise.

As is well known, however, unemployment persistence may also arise from spurious state dependence due either to the sampling scheme, unobserved explanatory variables which are correlated over time and/or the failure to account for 'initial conditions' in a dynamic context. Unless these factors are adequately controlled for, the correlation between an individual's unemployment experience and his future labour force status gives no information on a causal relationship as implied by structural state dependence.

Most empirical studies that have tried to test for state dependence effects in unemployment dynamics at the micro level are based on the estimation of hazard functions for single spells unemployment data (for a summary see Levine / Kiefer 1991; for an application to the German labour market see, e.g., Licht / Steiner 1991). Although these studies have yielded useful information, they provide only a partial description of an individual's labour force behaviour as they do not account for the incidence of multiple spells of unemployment. In the present paper we focus on this so far somewhat neglected aspect of unemployment dynamics.

To explain an individual's labour force behaviour within the period 1985 - 1989 we estimate a dynamic random-effects probit model based on the first six waves of the German Socio-Economic Panel and test for state dependence effects with respect to both an individual's labour force status in the previous period and the cumulated duration of past unemployment. It is shown that, after controlling for observed and unobserved population heterogeneity, there are strong state dependence effects in individual unemployment dynamics with respect to both the incidence and the duration of an individual's past unemployment.

The remainder of the paper proceeds as follows. In the next section the meaning of true and spurious state dependence is briefly explained, and the circumstances under which the latter may arise when analyzing individual unemployment dynamics with panel data are discussed. The econometric model is set out in section 3, and the data are presented in section 4. The main results of the paper are contained in section 5, and section 6 concludes with a summary.

2. Structural and spurious state dependence in unemployment dynamics

The question whether there is a causal relationship between an individual's past employment behaviour and his future labour force status is of considerable substantive interest in the theory of unemployment. The 'scar theory' of unemployment holds

> "that unemployment experience alters one's future probability of being unemployed because individuals lose valuable work experience while they are unemployed, or because they are marked as 'losers' by potential employers" (Heckman / Borjas 1980, p. 250).

One could add that the longer previous unemployment has lasted, the more likely it is that scars will become permanent as long-term unemployment may well amplify these effects.

If the 'scar theory' were an adequate description of individual unemployment dynamics, the popular view of the labour market characterized by efficient turnover and job-search activities would be called into question. Given its importance for both unemployment theory and policy, it comes as no surprise that this hypothesis has received a great deal of attention from economists and policy makers alike (see e.g. Heckman 1981; Ellwood 1982; OECD 1985).

Casual empiricism indeed seems to suggest that an individual who has recently experienced an unemployment spell is more likely to be also observed unemployed in the near future than someone who has never been unemployed. However, persistence in unemployment need not necessarily be due to causal factors, but may simply arise from spurious correlation, for which there are basically three possible sources (Heckman 1981a). Spurious state dependence may arise

(i) if the sampling scheme is such that a single unemployment spell, on average, overlaps between two consecutive periods,

(ii) if individual characteristics correlated with the propensity to experience unemployment are not adequately controlled for, or

(iii) if initial conditions or relevant presample history of the unemployment process are not taken into account.

We now briefly discuss these three points in turn. The dependent variable in our econometric model, which is described in detail in the next section, is an individual's labour force status at a given point in time. Hence, the sampling scheme is one of point sampling where our data base allows for roughly one year between two consecutive periods. Given an average duration of completed spells of unemployment within the observation period of about 5.8 months, this seems a sufficiently long period to avoid spurious state dependence arising from this source.

Heterogeneity is controlled for in our econometric model by conditioning on a number of personal characteristics and labour market indicators and by allowing for unobserved individual effects. Given the availability of panel data and the validity of certain assumptions about the distribution of these unobservables, consistent estimates of parameter estimates can be obtained.

There are several ways to deal with the 'initial conditions' problem which arises in a dynamic context when presample information on an individual's unemployment process is relevant for future behaviour (Heckman 1981c; Hsiao 1986, pp. 169). Here, we follow a suggestion by Heckman (1981b) and approximate the inital conditions by a reduced-form equation describing an individual's labour force status at the beginning of the oberservation period.

Having outlined the main problems encountered when testing for structural state dependence in individual unemployment dynamics, we now turn to the specification of the econometric model.

3. Econometric specification

In this section we present the statistical model we will use to analyze the employment history of adult men over a period of several years. Our analysis is based on the notion that discrete events are generated by latent continuous variables that cross thresholds. The latent variables may depend on observed exogenous and lagged endogenous variables as well as on unobserved disturbances, which potentially allows us to distinguish between structural state dependence and population heterogeneity. Our model is a slightly modified variant of the general approach developed by Heckman (1981a). For alternative approaches to the modelling of dynamic labour force behaviour with applications to the German labour market see Arminger (1992) and Mühleisen (1992).

Let $Y^*_{i,t}$ be a latent continuous variable for individual i in period t describing an individual's unemployment propensity. $Y^*_{i,t}$ is assumed to be a linear combination of the factors which determine whether individual i is employed or unemployed in period t. If $Y^*_{i,t} \geq 0$, the individual is unemployed, if $Y^*_{i,t} < 0$, the individual is employed.

We define a dummy variable $Y_{i,t}$:

$$(1) \quad Y_{i,t} = \begin{cases} 1, \text{ if } Y^*_{i,t} \geq 0 \\ 0, \text{ if } Y^*_{i,t} < 0 \end{cases}$$

In our model $Y^*_{i,t}$ depends on a vector $x_{i,t}$ of measured exogenous variables, on the employment realization $Y_{i,t-1}$ in the previous period and on a disturbance $v_{i,t}$:

$$(2) \quad Y^*_{i,t} = \beta' x_{i,t} + \gamma Y_{i,t-1} + v_{i,t} \qquad t = 1,\dots,T$$

The presence of the lagged outcome variable $Y_{i,t-1}$ allows us to test the hypothesis of true state dependence. This means that the event of being employed or unemployed may have a causal effect on the future employment history, due to effects on wealth, human capital, labour market experience etc.

For a given individual the error term may be serially correlated, which would lead to spurious state dependence as defined in the previous section. We assume that this autocorrelation is caused by an unobserved individual effect ε_i which represents unmeasured characteristics of individual i assumed to be constant over time. In order to test for true state dependence we have to control for this unobserved individual effect, otherwise a significant γ in equation (2) may simply be the result of information on the unobserved individual characteristics contained in the past occurence variable $Y_{i,t-1}$. In order to arrive at a tractable model we decompose $v_{i,t}$ as

$$(3) \quad v_{i,t} = \rho\varepsilon_i + u_{i,t}$$

where ρ measures the strength of the individual effect and ε_i as well as $u_{i,t}$ follow a multivariate normal distribution with:

$$\begin{array}{ll}
\mathrm{E}(\varepsilon_i) = \mathrm{E}(u_{i,t}) = 0 & \\
\mathrm{var}(\varepsilon_i) = 1 & \\
\mathrm{var}(u_{i,t}) = \sigma_u^2 & \\
\mathrm{cov}(\varepsilon_i, \varepsilon_j) = 0 & \text{for } i \neq j \\
\mathrm{cov}(u_{i,t}, u_{i,t'}) = 0 & \text{for } t \neq t' \\
\mathrm{cov}(\varepsilon_i, u_{i,t}) = 0 & \text{for all } i \text{ and } t
\end{array}$$

Furthermore, $v_{i,t}$ is assumed to be uncorrelated with the variables collected in x and independently distributed over all individuals. This one-factor random effects model implies that for individual i the v_i are equi-correlated: $\mathrm{cov}(v_{i,t}, v_{i,t'}) = \rho^2$.

Given ε_i, the conditional probability that $Y_{i,t} = 1$ is

$$(4) \quad \begin{array}{l}
\Pr(Y_{i,t} = 1 | x_{i,t}, Y_{i,t-1}, \varepsilon_i) = \Pr(Y_{i,t}^* \geq 0) = \\
\Pr(u_{i,t} \geq -(\beta' x_{i,t} + \gamma Y_{i,t-1} + \rho\varepsilon_i)) = \Pr(u_{i,t} / \sigma_u \leq \tilde{\beta}' x_{i,t} + \tilde{\gamma} Y_{i,t-1} + \tilde{\rho}\varepsilon_i)
\end{array}$$

with $\tilde{\beta} = \beta / \sigma_u$, $\tilde{\gamma} = \gamma / \sigma_u$ and $\tilde{\rho} = \rho / \sigma_u$.

Hence, in short-hand notation, we have

$$(4') \Pr(Y_{i,t} = 1 | x_{i,t}, Y_{i,t-1}, \varepsilon_i) = \Phi(z_{i,t}(\varepsilon_i))$$

with Φ the cumulative normal distribution and $z_{i,t}(\varepsilon_i) = \tilde{\beta}' x_{i,t} + \tilde{\gamma} Y_{i,t-1} + \tilde{\rho}\varepsilon_i$.

Given the value of ε_i, we can interpret the equations (2) as a recursive system. Therefore the conditional probalitity of an observed sequence $Y_i = (Y_{i,1}, Y_{i,2}, \ldots, Y_{i,T})$ is simply given by the product of the single conditional probabilities $\Pr(Y_{i,t} | x_{i,t}, Y_{i,t-1}, \varepsilon_i)$. To get the unconditional probability we multiply this product by the density function of ε_i and integrate with respect to ε_i:

$$(5)\ L_i = \int_{-\infty}^{\infty} \prod_{t=1}^{T} \left\{ \left[\Phi(z_{i,t}(\varepsilon_i))\right]^{Y_{i,t}} \left[1 - \Phi(z_{i,t}(\varepsilon_i))\right]^{1-Y_{i,t}} \right\} \varphi(\varepsilon_i) \mathrm{d}\varepsilon_i$$

with $\varphi(\varepsilon_i)$ the normal density function. The log-likelihood function for all observations $i, i = 1, \ldots, I$ is then given by

$$(6)\ L = \sum_{i=1}^{I} \ln L_i$$

The computation of the likelihood requires a numerical integration which is performed by using the Gauss-Legendre-procedure.

Under the maintained hypothesis of a multivariate normal distribution of ε_i and $v_{i,t}$ and a correct model specification the ML-estimator is consistent and asymptotically normal. The asymptotic variance-covariance matrix of the parameters can consistently be estimated by

$$(7)\ \hat{\Sigma}_\theta = -\left[\sum_{i=1}^{I} \left(\partial^2 \ln L_i / \partial\theta\partial\theta' \right) \right]^{-1}$$

where all parameters are collected in the vector θ.

One problem which remains to be discussed is the specification of the initial value $Y_{i,0}$. The simplest way to account for initial conditions is to define the problem away by assuming (i) the relevant presample history of the unemployment process to be truly exogenous, or (ii) the unemployment process to be in 'equilibrium' (Hsiao 1986, p. 169). Both of these assumptions seem too restrictive and should obviously be avoided. Dealing with it within a maximum likelihood framework, however, is rather involved. Heckman (1981c) presents several methods for handling the initial conditions problem. We follow his proposed simplified procedure and approximate the latent variable $Y^*_{i,0}$ by a linear function of presample information, collected in the vector $x_{i,0}$

$$(8)\ Y^*_{i,0} = \beta'_0 x_{i,0} + \rho_0 \varepsilon_i + u_{i,0}$$

with $u_{i,0} \sim \mathrm{N}(0, \sigma_{u0}^2)$. Hence, we augment the product in the likelihood function in eq. (5) by the term $\left[\Phi(z_{i,0}(\varepsilon_i))\right]^{Y_{i,0}}\left[1-\Phi(z_{i,0}(\varepsilon_i))\right]^{1-Y_{i,0}}$.

4. Description of the Data

The data of the present study come from the first six waves of the German Socio-Economic Panel (SOEP) which refers to the resident population of the former West-German states.[1] As the specification of our model only allows for a binary dependent variable and requires complete observations for each individual in all six waves, we restrict the analysis to males, excluding civil servants, the self-employed as well as men in vocational training schemes, between 25 and 51 years of age in 1984 and use a balanced panel design. The age restrictions are motivated by the institutional features of the German educational system and retirement schemes, the exclusion of civil servants by the fact that, as a rule, they do not become non-employed before retirement. Given that the model is estimated on a sample of middle-aged males for whom schooling or retirement are generally not feasible alternatives, the aggregation of all non-employment labour force states into a single category, simply called 'unemployment', does not seem critical.[2]

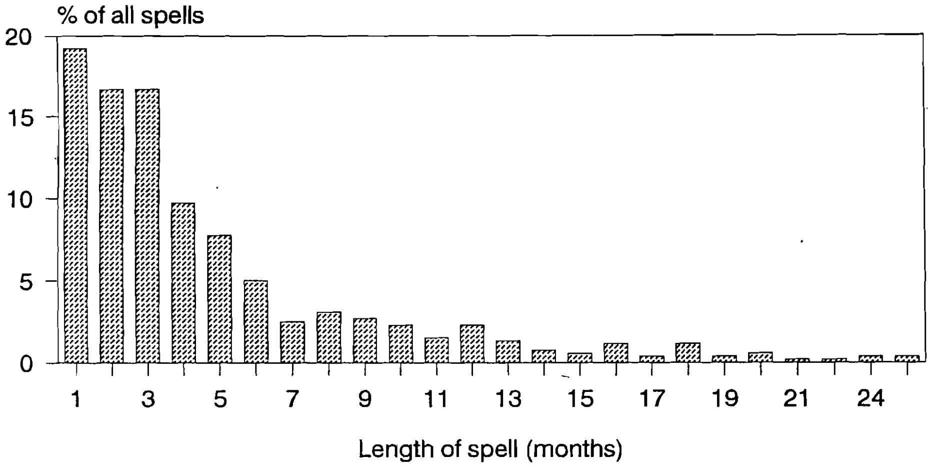
The SOEP contains detailed information on an individual's labour force status at the date of interview in each wave within the six-year period 1984 to 1989 as well as the number and completed durations of all unemployment spells within this period, the distributions of which are plotted in figures 1 and 2. In addition, the SOEP contains detailed information on individual characteristics usually included in unemployment studies at the micro level. Details on the definition of variables and summary statistics are supplied in Table 1.

Figure 1 shows the frequency distribution of completed unemployment spells between January 1983 and December 1988 for our sample of middle-aged men. The plot covers 97.3 % of all 515 completed unemployment spells. As some fairly long spells with a duration of more than 25 months are not contained, the distribution is truncated from the right side. The mean duration of the spells amounts to 5.7 months. The figure cleary shows that the bulk of the spells is relatively short in nature: 75.5 % of the spells are not longer than six months. This points to a high turnover in the unemployment pool, i.e. a vast majority of males becoming unemployed will leave this state relatively quickly. On the other hand, there is a considerable relatively stock of unemployed males who suffer rather long periods of unemployment.

1 For a description of the SOEP see Wagner / Schupp / Rendtel (1991).

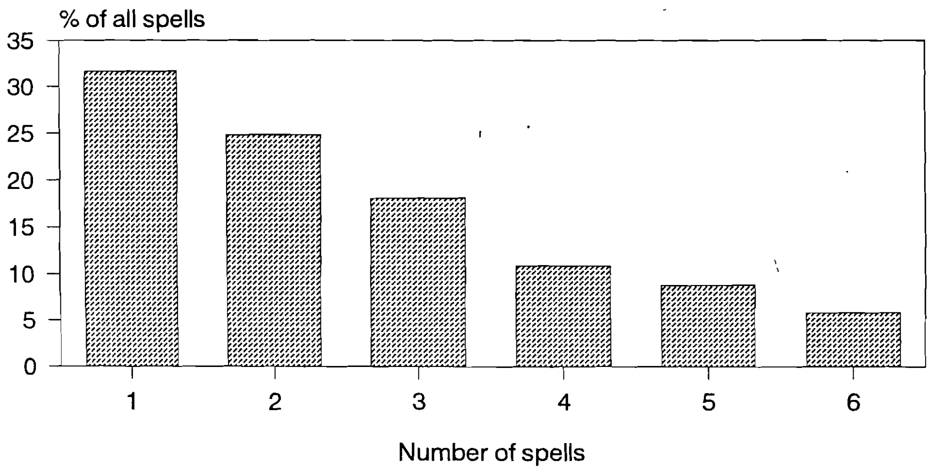
2 In contrast, female employment behaviour can probably not be adequately explained within the chosen framework because (temporary) withdrawals from the labour market associated with household and child rearing responsibilities are quite frequent for females. Furthermore, the balanced panel design would result in a relatively small sample size for the female subsample.

FIGURE 1: The distribution of durations of all completed unemployment spells 1984 - 1989



Source: Socio-Economic Panel, waves 1 - 6, own calculations.

FIGURE 2: The distribution of completed unemployment spells 1984 - 1989



Source: Socio-Economic Panel, waves 1 - 6, own calculations.

Figure 2 shows the distribution of the number of unemployment spells per individual over the same period. It highlights the occurence of repeated spells of unemployment, which is often neglected in empirical research. As only about 30 % of the unemployed males have a single spell, we can conclude that multiple spells are more a rule than an exception. This stresses the importance of a dynamic modelling strategy to uncover some causal factors underlying these facts.

The dependent variable in our empirical model is an individual's labour force status, LFSTAT, at the date of interview in each year, aggregated into the categories 'employed' and 'non-employed'. Conditioning on an individual's lagged labour force status, LFSTATL, we cannot use the first wave which was conducted in 1984 for estimating the structural probit model. As discussed in the previous section, this information will, however, be used to model initial conditions determining an individual's labour force status at the start of the observation period.

In order to allow an individual's unemployment probability to depend on the duration of past unemployment, we have included an individual's cumulated unemployment experience within the past two years, CDURL, as explanatory variable in our model. To avoid or at least to reduce the length-bias associated with sampling from a stock of unemployed, the reference period for calculating CDURL spans half a year after the month the interview has taken place in the previous wave and one and a half year before that date. Given that the average duration of an unemployment spell is less than six months, this construction will mitigate the danger of LFSTAT and CDURL being correlated by construction.

Besides an individual's lagged labour force status and the duration of unemployment within the past two years the set of explanatory variables in the structural probit equation includes household income other than own earnings, HINC, personal characteristics and some labour market indicators. HINC income clearly acts as a supply-side variable by affecting an individual's labour supply decision, which may also be true for age, nationality, health and marital status.

The latter variables and, somewhat more objectively, education and vocational training may also act as signals for an individual's productivity and thus influence his chance of being offered a job. Being a white collar worker ('Angestellter') is expected to increase an individual's employment probability. Of course, some of these variables may catch both demand-side and supply-side effects on individual employment behaviour, which renders interpretation of results somewhat difficult without imposing more structure onto the model.

Table 1 Definition of Variables and Summary Statistics

Variables names	Description of variables	Mean	Standard deviation
LFSTAT	Labour force status; 0 = employed, 1 = unemployed (nonemployed)	0.076	
LFSTATL	Labour force status at the date of last year's interview	0.075	
Unemployment Experience			
CDURL	Observed cumulated unemployment duration between 2.5 years before and 0.5 years before the month of interview	2.001	5.680
CDURLP	Perdicted values of cumulated unemployment duration (see Table A3)	1.897	5.388
LCEN	= 1, if CDURL is cencored at left side	0.071	
RCEN	= 1, if CDURL is cencored at right side	0.083	
NUN84L	Number of unemployment spells during 1974 - 1984	0.415	1.137
DUR84L	Cumulated unemployment duration during 1974 - 1984 (in months)	2.292	6.794
Household Characteristics			
HINC	Real net monthly household income minus own net earnings (in 1000 DM)	1.026	1.704
FSTAT	= 1, if married		0.853
CHILD	Number of children living in household	1.033	1.133
Personal Characteristics			
NAT	= 1, if foreigner		0.385
AGE	Age in years		41.177
HEALTH	= 1, if disabled		0.074
Schooling and vocational training (highest degree)			
EDUC1	Elementary school (Hauptschule)		0.108
EDUC2	Grammar school (Gymnasium, Fachoberschule, u._)	0.092	
Ref. Group	High school (Realschule, Fachschule)	0.800	
TRAIN 1	Vocational training less than three years	0.587	
TRAIN 2	University degree	0.138	
Ref. Group	Three years of vocational training	0.275	
WHITE	= 1, if white collar worker (Angestellter)	0.308	
Regional Labour Market Indicators			
EGROWY	Yearly growth rate of regional employment at month of interview (in percent)	0.365	1.689
EGROWQ	Quarterly growth rate of regional employment at month of interview	0.803	1.270
UNRATIO	Regional unemployment rate	0.095	0.026
Regional dummies ('Bundesländer')			
SH/HH	Schleswig-Holstein, Hamburg	0.056	
HB/NS	Bremen, Niedersachsen	0.098	

continued ⇒

Table 1 continued

Variables names	Description of variables	Mean	Standard deviation
HESS	Hessen	0.110	
RP/S	Rheinland-Pfalz, Saarland	0.073	
BW	Baden-Württemberg	0.200	
BAV	Bayern	0.153	
BERLIN	Berlin	0.029	
Ref. Group	Nordrhein-Westfalen	0.281	
Urban agglomeration dummies (household's residence)			
BOU1	Metropolitan areas with 50,000 to 500,000 inhabitants	0.176	
BOU2	Rural region (less than 50,000 inhabitants)	0.332	
Ref. Group	Large metropolitan areas (more than 500,000 inhabitants)	0.492	

Aggregate demand-side effects on individual employment behaviour are accounted for by regional unemployment rates and quarterly and yearly growth rates of regional employment. In addition, we also include dummies for region of residence and indicators for urban agglomeration as control variables in our extended model specification.

The set of explanatory variables in the reduced-form probit equation for the initial conditions also include HINC and the usual personal characteristics. The information contained in the first wave of the SOEP allows us to include an individual's cumulated duration and number of spells of unemployment within the ten years prior to the date of the first interview in 1984. The latter variables, in particular, are expected to effectively control for initial unobserved individual differences in employment behaviour.

5. Results

5.1 Testing the specification

We first estimated a rather general specification of the RE probit model by including all the variables referred to in the previous section within the set of explanatory variables.[3] Estimation results for this extended model specification are contained in Table A1 in the appendix.

A likelihood ratio test for the extended model specification clearly rejected the null hypothesis that the heterogeneity component in the structural probit is insignificant (see Table 2). However, with one exception, estimation results for this model do not differ much from those obtained from a simple probit model pooled over all

[3] To obtain starting values we first estimate the structural model pooled over the period 1985-1989 by OLS and the initial condition using the 1984 data only. A transformation of the OLS coefficients are used as starting values for the probit model with the individual effects constrained to zero. The estimated parameter vector of this model are used as starting values for the RE-probit model. GAUSS 2.0 was used for all estimations.

waves, this exception being the coefficient on LFSTATL in the first column of Table A1 which increases from 0.967 to 1.144 (not shown in the tahle). Given its relatively large standard error, this does not seem to be statistically significant.

Table 2 Testing for individual effects and endogeneity of past unemployment duration

	Extended Model	Restricted Model
Individual effects	13.26 (2)	15.05 (2)
Endogeneity	140.89 (2)	139.50 (2)

Note: Likelihood-ratio statistic; Degrees of freedom in parentheses.

The cumulated duration of unemployment an individual has experienced within a two years period in the past, CDURL, may well be affected by the same unobserved factors as his current labour force status. Therefore, the inclusion of this variable in the RE probit model is suspected to result in simultaneity bias. The results of a standard variables addition test (Wu 1973) indeed showed that CDURL cannot be treated as exogeneous in the econometric sense (see Table 2). We therefore instrumented this variable, where we proceeded along the following lines.

An instrument for CDURL was constructed by regressing this variable on HINC, personal characteristics, the number and duration of an individual's unemployment before 1984, and several labour market variables. We also included dummy variables which take a value of one if CDURL is censored from the left and / or from the right. As the bulk of the respondents in the sample has never been unemployed within the respective reference period, estimation is based on cross-section reduced-form tobit models.

Estimation results for the reduced-form tobit models for the years 1985 to 1989 will not be discussed in any detail here, but are reported in Table A3. Based on these estimates we have calculated the expectation for CDURL and its square which were then used as regressors in the second-step estimation of the RE-probit model. Although estimated coefficients vary a great deal between the cross-sections, this has little effect on the constructed instruments which is shown by the means, standard deviations of the instruments and their correlations with CDURL in each wave which are also reported in Table A3.

Results for the instrumented version of the extended specification of the model are contained in Table A1. Although the exogeneity assumption for CDURL is clearly rejected by a Wu-test (see Table 2), it turns out that instrumenting this variable (and its square) does not significantly change estimation results, the exception being the estimate for the heterogeneity component in the structural probit, $\tilde{\rho}$, which nearly doubles in size. It seems interesting to note that restricting the heterogeneity component to zero in this specification would significantly raise the estimated coefficient on LFSTATL from 1.099 to 1.423 (with an estimated standard error of 0.099).

Given these results, and in order to test efficiently for unobserved heterogeneity and state dependence effects, we then searched for a reasonably parsimoneous model specification compatible with the data, where our starting point was the extended instrumented RE probit model in Table A1. Following the sequential test procedure described in Figure A2 in the appendix, we have simplified the latter model using standard Wald (t-tests) for single variables and likelihood-ratio tests for groups of variables. The criteria for the exclusion has been a t-value of less than one and a prob-value for the latter test statistic larger than 10 percent.

We ended up with the restricted model summarized in Table 3 where NAT, EDUC1, EDUC2, TRAIN1, TRAIN2, and the dummies for region and urban agglomeration are excluded from the structural probit equation. Although t-values of AGE and AGESQ are very low, they happen to be jointly significant at the 5 percent level, and can therefore not be dropped from the specification. The regional unemployment rate and the quarterly employment growth rate also remained in our final specification because both variables, although showing insignificant t-values, are best interpreted together with the yearly employment growth rate. The same also holds for NUN84L, the number of unemployment spells in the ten-year period before 1984, which is best interpreted together with their cumulated durations, DUR84L. For the remaining variables, estimated coefficients in the extended and restricted versions of both the model with CDURL and that with this variable instrumented turned out very similiar.

Table 3 Dynamic Random Effects Probit Model for Individual Unemployment Behaviour - Restricted Specification

	Standard RE Probit		IV-RE Probit	
	Coefficient	t-value	Coefficient	t-value
	Structural Equation			
CONSTANT	-1.696	-1.51	-2.463	-1.84
$\tilde{\rho}$	0.369	2.57	0.636	5.56
LFSTATL	0.971	5.72	1.097	7.77
CDURL	0.195	10.25	0.230	11.30
CDURLSQ	-0.487	-6.55	-0.504	-7.06
HINC	0.077	6.95	0.083	6.61
AGE	-0.025	-0.44	-0.001	-0.02
AGESQ	0.048	0.70	0.024	0.29
FSTAT	-0.259	-2.62	-0.283	-2.37
HEALTH	0.445	3.89	0.398	2.88
WHITE	-0.441	-4.62	-0.558	-4.86
UNRATIO	-1.158	-0.86	-1.202	-0.79
EGROWJ	-0.075	-1.93	-0.108	-2.46
EGROWQ	-0.037	-1.42	-0.033	-1.11

continued ⇒

Table 3 continued

	Standard RE Probit		IV-RE Probit	
	Coefficient	t-value	Coefficient	t-value
		Initial Condition		
CONST	2.108	1.12	2.153	1.13
$\tilde{\rho}$	0.134	0.64	0.122	0.79
DUR84L	0.117	6.31	0.117	6.35
DUR84LSQ/100	-0.094	-2.28	-0.093	-2.27
NUN84L	-0.052	-0.93	-0.052	-0.93
HINC	0.141	4.87	0.141	4.87
AGE	-0.229	-2.21	-0.231	-2.19
AGESQ	0.292	2.14	0.295	2.12
HEALTH	0.591	2.65	0.595	2.68
EDUC1	-0.325	-1.28	-0.322	-1.27
EDUC2	0.835	3.48	0.835	3.49
WHITE	-0.650	-3.17	-0.649	-3.18
No. of indivduals	1246		1246	
No. of observations	7476		7476	

Finally, we tested this restricted specification for the presence of individual effects and the endogeneity of CDURL. A likelihood ratio test for this model clearly rejected the null hypothesis that the heterogeneity components in the structural and in the reduced-form probits are insignificant (see Table 2). Furthermore, a Wu-test clearly rejects the null hypothesis of exogeneity of CDURL. However, as in the extended specification of the model, instrumenting this variable (and its square) does not significantly change estimation results, the exception again being the estimate for the heterogeneity component in the structural probit.

Likewise, restricting the heterogeneity component to zero in this model would have pretty much the same effect as in the extended specification; the estimated coefficient on LFSTATL would be increased significantly from 1.097 to 1.439 (with an estimated s.e. of 0.092). It may be interesting to note that a similiar result has also been obtained by Narendranathan / Elias (1990) in their study of youth for the UK, where the estimated coefficient on the lagged (by one period) indicator variable in a RE logit model increased significantly from 0.83 to 1.99 in their model without unobserved heterogeneity.

From the results presented so far we conclude that the instrumented version of the specification in Table 3 gives the most reliable estimates of all the tested models. The following interpretation of estimation results is therefore based on this model.

5.2 State dependence effects and unobserved heterogeneity

To start with the heterogeneity component, note that it has a highly significant effect on an individual's unemployment probability in the structural probit, but is insignificant in the reduced-form probit equation for the initial conditions. A possible explanation for the insignificance of the heterogeneity component in the latter equation is that the inclusion of relevant presample information on an individual's past unemployment history, represented by the variables DUR84L, its square and NUN84L, effectively controls for the factors affecting his labour force status at the beginning of the observation period. This interpretation is also suggested by the rather high t-value on DUR84L.

This interpretation is also confirmed by re-estimation of the model leaving out these variables from the reduced probit equation. The individual effect in the initial condition triples in size and becomes highly significant, whereas there are no significant changes in the coefficients and standard errors of the other variables.

As the focus of the present study is on state dependence effects and unobserved heterogeneity, discussion of estimation results with respect to most explanatory variables in the model will be brief here[4]. Overall, estimated coefficients have the expected sign and are of reasonable magnitude in both the structural and reduced-form probit equation. As expected, a higher household income other than own earnings increases the probability that an individual is not working, ceteris paribus. It declines with age (at a decreasing rate), is significantly lower for married males and white collar workers, and is greatly increased if an individual reports health problems. The schooling variables have no significant effect on an individual's employment probability within the observation period, but affect initial conditions.

Estimation results for the regional labour market indicators, which only play a role in the structural probit, are less clear-cut. Whereas the negative, although insignificant coefficient of the regional unemployment variable comes as a surprise, the estimated effects of the yearly and quarterly growth rates of regional employment are in line with intuition.

As expected, an individual's current employment status is strongly dependent on his state in the previous period. Evaluated at variable means, the unemployment probabilitiy for someone who has been employed at the date of the previous interview increases from 1 percent to 10 percent if this person has been unemployed. This persistence effect is comparable in size with the estimate of Narendranathan and Elias (1990) in their study of youth unemployment in the UK who also have found a rather dramatic effect. This occurence dependence effect is illustrated in Figure 3.

In Figure 3 the development of the unemployment probability for someone unemployed in the base period is compared to the unemployment probability of an employee in the base period. All other variables - including both lagged duration dependence variables - are evaluated at variable means. The assumed value of the

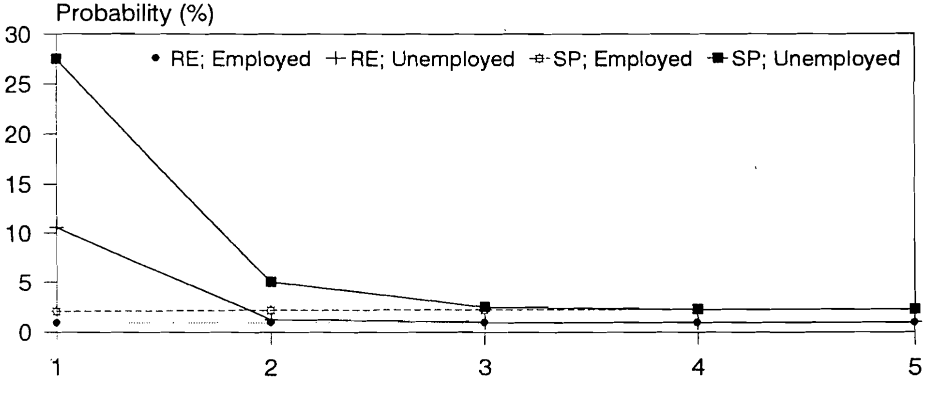
4 Mühleisen (1992), using a different methodology, finds similar results for West Germany.

individual effect in the random effects probit modell is zero. The figure clearly shows the remarkable state dependence effect in the first year. But it can also be seen that this effect nearly vanishes within a few years after the occurence of unemployment when the unemployment probability converges to its steady state value. Changing the random effect would alter the steady state value.

Figure 3 also demonstrates the importance of controlling for unobserved heterogeneity. The unemployment probability estimated from the simple probit model (SP) would increase from 2 percent to 28 percent in the first year following an unemployment occurence and will also be noticeable in the second year. Therefore, one can conclude that a failure to control for unobserved heterogeneity would lead to severly biased estimates of the occurence dependence effect.

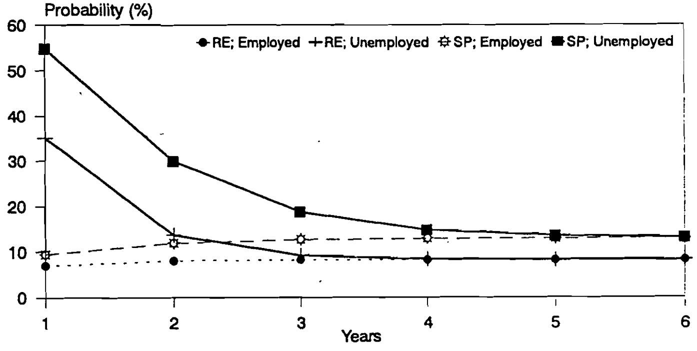
There is also a strong persistence effect with respect to the duration of past unemployment, a result which has also been found by Mühleisen (1992). The longer the cumulated duration of unemployment within the reference period, the more likely an individual will also be unemployed in the future. Evaluated at variable means, the probability of unemployment increases for someone who is employed at the date of the previous interview from 2 % to 6.9 % if CUMDL is raised from 1.9 month, its overall mean value, to 5.8 month, which represents the mean duration of an unemployment spell. If the individual was unemployed at the date of last interview the unemployment probability would increase from 10 percent to about 35 percent. This is illustrated in Figure 4 where the overall mean of the lagged duration variable is substituted by the mean duration of unemployment spells. Compared to Figure 3 it can be seen that the lagged duration dependence effect reinforces the occurrence dependence effect in the sense that the size and duration of the latter on individual unemployment behaviour are the more pronounced the longer the duration of past unemployment is.

FIGURE 3: Unemployment probabilities, occurence dependence and unobserved heterogeneity



Note: Estimation is based on partial effects only;
RE = Random Effects Probit, SP = Simple Pooling Probit

FIGURE 4: Unemployment probabilities, occurence and lagged duration dependence and unobserved heterogeneity



Note: Estimation is based on partial effects only;
RE = Random Effects Probit, SP = Simple Pooling Probit

6. Summary and conclusion

The paper has stressed the distinction between true or 'structural' and spurious state dependence in male unemployment dynamics. In particular, we have tested whether an individual's unemployment probability at a given point in time depends on his labour force status in the previous period and on the cumulated duration of past unemployment in a causal way or is rather due to serially correlated explanatory variables and / or unobserved individual effects. Although of considerable interest to both labour economists and labour market policy, this question has so far received little attention in empirical work on the incidence of multiple spells of unemployment, especially for the German labour market.

To test for structural state dependence effects in male unemployment behaviour we have estimated a dynamic random effects probit model on the first six waves of the German Socio-Economic Panel, where estimation is based on the marginal likelihood approach. It is shown that, after controlling for observed and unobserved population heterogeneity, there are strong state dependence effects with respect to both the incidence and the duration of an individual's past unemployment.

These results are compatible with the 'scar theory' of unemployment which holds that an individual's previous unemployment experience may have long-term effects because it results in a depreciation of human capital and/or acts as a screening device in employers hiring decisions. Given that the incidence of previous unemployment, and especially of long-term unemployment in the recent past, impairs an individual's future employment prospects, labour market theories which explain unemployment with efficient job search activities and labour turnover seem less convincing. Furthermore, labour market policies which prevent (long-term) unemployment to develop in the first place may well have positive long-term effects.

Appendix

Table A1 Dynamic Random Effects Probit Model for Individual Unemployment Behaviour - Extended Specification

	Standard RE-Estimates		IV-Estimates	
	Coefficient	t-value	Coefficient	t-value
	Structural Equation			
CONSTANT	-1.765	-1.43	-2.612	-1.81
IND.EFFECT	0.356	1.96	0.619	4.76
LFSTATL	0.967	4.48	1.099	6.70
CDURL	0.190	10.27	0.226	10.61
CDURLSQ	-0.465	-6.46	-0.490	-6.87
HINC	0.076	2.65	0.082	2.72
AGE	-0.024	-0.38	-0.001	-0.00
AGESQ	0.047	0.60	0.023	0.26
NAT	0.039	0.43	0.092	0.87
FSTAT	-0.271	-2.80	-0.301	-2.73
HEALTH	0.451	4.18	0.407	3.20
EDUC1	0.080	0.70	0.075	0.54
EDUC2	0.074	0.34	0.068	0.26
TRAIN1	-0.031	-0.36	0.025	0.24
TRAIN2	-0.107	-0.52	0.051	0.20
WHITE	-0.405	-3.18	-0.544	-3.66
UNRATIO	-1.091	-0.82	-1.106	-0.76
EGROWY	-0.082	-1.77	-0.111	-2.13
EGROWQ	-0.041	-1.37	-0.038	-1.18
BOU1	0.043	0.41	0.041	0.33
BOU2	0.136	1.58	0.170	1.61
SH/HH	0.108	0.70	0.166	0.84
HB/NS	0.036	0.26	0.101	0.61
HESS	-0.038	-0.28	-0.049	-0.30
RP/S	-0.285	-1.75	-0.193	-0.98
BW	-0.059	-0.46	-0.059	-0.38
BAV	0.069	0.56	0.095	0.65
BERLIN	0.149	0.83	0.159	0.72
	Initial Condition			
CONSTANT	1.373	0.71	1.425	0.76
IND.EFFECT	0.132	0.61	0.119	0.77
DUR84L	0.118	7.20	0.117	7.18
DUR84LSQ	-0.100	-2.74	-0.099	-2.70
NUN84L	-0.038	-0.66	-0.037	-0.65
HINC	0.134	2.93	0.134	2.92
AGE	-0.199	-1.93	-0.202	-2.02
AGE	0.257	1.89	0.260	1.98
NAT	-0.107	-0.55	-0.106	-0.54
FSTAT	-0.093	-0.50	-0.090	-0.50

continued ⇒

Table A1 continued

	Standard RE-Estimates		IV-Estimates	
	Coefficient	t-value	Coefficient	t-value
HEALTH	0.623	2.70	0.626	2.73
EDUC1	-0.316	-1.22	-0.312	-1.21
EDUC2	0.961	3.01	0.959	3.01
TRAIN1	-0.173	-1.00	-0.172	-0.99
TRAIN2	-0.438	-1.06	-0.433	-1.06
WHITE	-0.600	-2.36	-0.600	-2.39
UNRATIO	3.223	1.08	3.202	1.07
EGROWY	-0.021	-0.32	-0.021	-0.31
EGROWQ	0.025	0.69	0.025	0.69
BOU1	0.263	1.35	0.259	1.33
BOU2	-0.079	-0.46	-0.083	-0.48

Table A2 Dynamic Simple Probit Model for Individual Unemployment Behaviour - Restricted Specification

	Standard RE-Estimates		IV-Estimates	
	Coefficient	t-value	Coefficient	t-value
		Structural Equation		
CONSTANT	-1.830	-1.85	-2.695	-2.67
LFSTATL	1.160	12.07	1.439	15.69
CDURL	0.184	10.09	0.190	12.91
CDURLSQ	-0.475	-6.15	-0.440	-6.99
HINC	0.072	17.82	0.068	15.58
AGE	-0.013	-0.28	0.025	0.52
AGESQ	0.033	0.57	-0.011	-0.18
FSTAT	-0.241	-2.61	-0.231	-2.37
HEALTH	0.402	3.58	0.315	2.59
WHITE	-0.402	-5.64	-0.445	-6.22
UNRATIO	-1.089	-0.76	-0.810	-0.54
EGROWY	-0.067	-1.90	-0.085	-2.40
EGROWQ	-0.038	-1.68	-0.039	-1.67
		Initial Condition		
CONSTANT	2.076	0.96	2.077	0.96
DUR84L	0.116	5.20	0.116	5.19
DUR84LSQ	-0.093	-1.81	-0.093	-1.81
NUN84L	-0.048	-0.72	-0.048	-0.73
HINC	0.142	6.62	0.142	6.65
AGE	-0.227	-1.92	-0.227	-1.93
AGESQ	0.289	1.87	0.289	1.89
HEALTH	0.602	2.67	0.602	2.72
EDUC1	-0.328	-1.22	-0.328	-1.21
EDUC2	0.827	3.01	0.827	3.02
WHITE	-0.640	-3.49	-0.640	-3.50

Table A 3 Reduced-Form Cross-Section Tobit Models for Cumulated Duration of Previos Unemployment

Variables[2]	Dependent Variable: Lagged Duration of Unemployment (CDURL)[1] 1985	1986	1987	1988	1989
Variance	32.334	49.602	48.547	47.245	41.751
	(9.11)	(10.57)	(8.48)	(8.38)	(7.67)
CONS	9.681	4.210	7.371	5.732	-18.999
	(1.34)	(0.48)	(0.77)	(0.58)	(-1.78)
RCEN	16.408	17.980	19.390	17.868	18.662
	(20.16)	(18.93)	(19.38)	(16.40)	(17.28)
LCEN	11.167	13.261	13.647	15.653	14.119
	(13.63)	(10.75)	(13.96)	(13.98)	(13.70)
Unemployment history					
NUN84L	0.166	0.933	1.335	0.418	0.958
	(0.64)	(3.33)	(4.89)	(1.51)	(3.40)
DUR84L	0.427	0.526	0.067	0.438	0.104
	(4.51)	(5.36)	(0.78)	(4.44)	(1.14)
DUR84LSQ	-0.631	-1.024	-0.204	-0.957	-0.098
	(-3.56)	(-6.27)	(-0.93)	(-5.20)	(-0.48)
Household Characteristics					
HINC	0.270	1.196	0.156	0.118	0.415
	(2.00)	(3.91)	(1.66)	(1.18)	(2.17)
Personal Characteristics					
AGE	-1.043	-0.787	-0.845	-0.851	0.383
	(-2.69)	(-1.67)	(-1.73)	(-1.75)	(0.74)
AGESQ	0.254	0.891	0.958	1.074	-0.456
	(2.47)	(1.47)	(1.57)	(1.84)	(-0.74)
EDUC1	0.349	0.629	-0.034	-0.949	0.162
	(0.32)	(0.56)	(-0.03)	(-0.86)	(0.16)
EDUC2	0.488	0.959	-0.316	1.195	-1.223
	(0.59)	(0.73)	(-0.26)	(0.99)	(-0.95)
TRAIN1	0.216	-0.910	0.104	-1.053	-0.639
	(0.31)	(-1.10)	(0.13)	(-1.42)	(-0.91)
TRAIN2	1.855	-1.892	0.493	-2.494	1.147
	(1.99)	(-1.40)	(0.41)	(-2.18)	(0.91)
HEALTH	1.620	2.453	0.777	-0.025	0.123
	(1.53)	(1.85)	(0.63)	(-0.03)	(0.12)

continued ⇒

Table A3 continued

Variables[2]	Dependent Variable: Lagged Duration of Unemployment (CDURL)[1] 1985	1986	1987	1988	1989
<u>Regional Labour Market Indicators</u>					
EGROWY	-0.498	0.053	-0.383	1.262	-0.506
	(-0.97)	(0.16)	(-0.32)	(1.71)	(-0.40)
EGROWQ	0.569	0.138	-0.082	-0.030	0.208
	(2.77)	(0.67)	(-0.28)	(-0.12)	(0.85)
<u>Regional Dummies</u>					
SH/HH	-1.569	1.511	2.289	3.153	1.651
	(-0.74)	(1.12)	(1.48)	(2.51)	(1.17)
HB/NS	-0.338	3.690	-0.253	0.608	0.875
	(-0.29)	(2.96)	(-0.21)	(0.44)	(0.71)
HESS	1.680	0.634	0.112	-2.250	-0.390
	(1.87)	(0.43)	(0.08)	(-1.58)	(-0.34)
RP/S	0.980	-2.606	-1.111	1.061	0.332
	(0.82)	(-1.56)	(-0.7)	(0.6)	(0.25)
BW	-1.700	-0.721	-1.258	-2.733	-0.753
	(-1.70)	(-0.52)	(-0.79)	(-2.27)	(-0.64)
BAV	0.200	1.667	-0.073	-0.332	1.960
	(0.18)	(1.63)	(-0.06)	(-0.21)	(1.48)
BERLIN	0.305	0.775	-0.979	-0.765	-1.529
	(0.19)	(0.42)	(-0.41)	(-0.38)	(-0.58)
<u>Urban Agglomoration Dummies</u>					
BOU1	-0.306	0.168	1.842	-0.037	0.656
	(-0.38)	(0.19)	(2.04)	(-0.04)	(0.79)
BOU1	0.514	1.617	1.591	0.502	1.088
	(0.75)	(1.99)	(1.98)	(0.62)	(1.53)
<u>Summary Statistics:</u>					
LR-Statistics[3]	862.1 (24)	789.2 (24)	774.4 (24)	781.2 (24)	906.9 (24)
McFaddens R^2	0.350	0.293	0.297	0.310	0.348
No. Observations	1246	1246	1246	1246	1246
Mean of CDURL	1.69	1.96	2.04	2.05	2.24
Std.Dev. of CDURL	5.00	5.51	5.72	5.87	6.23

continued ⇒

Table A3 continued

Variables[2]	Dependent Variable: Lagged Duration of Unemployment (CDURL)[1] 1985	1986	1987	1988	1989
Mean of CDURLP	1.62	1.86	1.92	1.92	2.14
Std.Dev. of CDURLP	4.74	5.12	5.41	5.62	5.97
Correlation of CDURL and CDURLP	0.90	0.86	0.89	0.91	0.92

NOTES: 1) Number of months spend unemployed between 1.5 years before and 0.5 years after the month of the previous interview.
2) t-values are in paranthesis.
3) The Likelihood-ratio statistics is based on the difference of the likelihood of the full model and the likelihood of a model including only a constant; Degrees of freedom in parenthesis.

FIGURE A1: Testing for a Parsimonious Specification of the Model

This table summarizes the performed variables exclusion tests. Starting from the IV-estimate of the extended model presented in Table A1, we excluded stepwise the mentioned variables below. The table gives the log. likelihood values and the number of variables (in paranthesis) included in the specification. We drop a (group) of variable(s) if it is indicated by a low likelihood ratio statistic. The selection of variables for the exclusion tests is guided by small t-values. SE (IC) means a variable is excluded from the structural equation (initial condition).

Extended Model
-951.5 (49)

Excluded Variables
SE: AGE, AGESQ
IC: None
-956.5 (43)

Excluded Variables
SE: EDUC1, EDUC2, TRAIN1, TRAIN 2
IC: None
-951.7 (45)

Excluded Variables
SE: EDUC1, EDUC2, TRAIN1 TRAIN2, AGE, AGESQ
IC: None
-956.5 (43)

Excluded Variables
SE: EDUC1, EDUC2, TRAIN1 TRAIN2, NAT
IC: None
-952.1 (44)

Excluded Variables
SE: EDUC1, EDUC2, TRAIN1, TRAIN2
IC: AGE, AGESQ, EGROWY. EGROWQ UNRATIO
-952.6 (40)

Excluded Variables
SE: EDUC1, EDUC2, TRAIN1 TRAIN2, NAT, AGE, AGESQ
IC: None
-957.2 (42)

Excluded Variables
SE: EDUC1, EDUC2, TRAIN1 TRAIN2, NAT
IC: EGROWY, EGROWQ, UNRATIO, NAT
-953.1 (40)

Excluded Variables
SE: EDUC1, EDUC2, TRAIN1, TRAIN2, NAT, Regional dummies
IC: EGROWY, EGROWQ, UNRATIO, NAT
-955.0 (33)

Excluded Variables
SE: EDUC1, EDUC2, TRAIN1, TRAIN2, NAT, Regional dummies
IC: EGROWY, EGROWQ, UNRATIO, NAT, FSTAT
-955.1 (32)

Excluded Variables
SE: EDUC1, EDUC2, TRAIN1, TRAIN2, NAT, Regional dummies
IC: EGROWY, EGROWQ, UNRATIO, NAT, FSTAT. BOU1, BOU2
-956.5 (30)

Excluded Variables
SE: EDUC1, EDUC2, TRAIN1, TRAIN2, NAT, Regional dummies, BOU1, BOU2
IC: EGROWY, EGROWQ, UNRATIO, NAT, FSTAT, BOU1, BOU2
-956.5 (28)

Excluded Variables
SE: EDUC1, EDUC2, TRAIN1, TRAIN2, NAT, Regional dummies, BOU1, BOU2
IC: EGROWY, EGROWQ, UNRATIO, NAT, FSTAT, BOU1, BOU2, TRAIN1, TRAIN2
-958.4 (26)

Excluded Variables
SE: EDUC1, EDUC2, TRAIN1, TRAIN2, NAT, Regional dummies, BOU1, BOU2, AGE, AGESQ
IC: EGROWY, EGROWQ, UNRATIO, NAT, FSTAT, BOU1, BOU2 TRAIN1, TRAIN2
-963.2 (24)

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