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Heterogeneity in unemployment state dependence

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HIGHLIGHTS

- This paper shows that unemployment state dependence is heterogeneous across workers.
- Assuming a homogeneous effect of past unemployment underestimates the *scarring* effect of unemployment.
- We apply a heterogeneous slope model to data from the ECHP on prime aged men.
- Individuals with a lower unemployment risk in their unobservables evaluate their spells of unemployment more negatively.

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ABSTRACT

By applying a heterogeneous slope model, this paper shows that unemployment state dependence varies across workers. Assuming a homogeneous effect of past unemployment on the risk of staying unemployed underestimates the *scarring* effect of unemployment in the majority of countries analyzed.

1. Introduction

Unemployment persistence has been the object of analysis by multiple scholars before (Arulampalam et al., 2000 and Biewen and Steffes, 2010). From that research, we have learnt that, besides the influence of observed and unobserved characteristics, unemployment suffers from a considerable degree of *genuine state dependence* by which an unemployment spell increases, in itself, the probability of someone being out of the labor force again in the future. The mechanisms behind such a scarring effect of unemployment are possibly much more difficult to disentangle, but several explanations have been pointed to in this research field: a loss of human capital, unemployment insurance disincentives, stigmatization by employers, a decline in search intensity, habituation or discouragement, among others.

Importantly, most of the literature that has attempted to measure state dependence in unemployment has always assumed that such an effect is homogeneous across individuals — with the only exceptions being Stewart (2007) that applies a heterogeneous slope model and Browning and Carro (2014) that presents a maximal heterogeneity model.[1] From research on the psychological and social effects of unemployment it is well known that unemployment represents a threat to the individual's personality, and that "coping strategies (...) play a part in how strongly people suffer as a result of unemployment" (Schöb, 2013, 153). Several internal and external factors such as, for example, the reason for exiting the labor market (voluntary or involuntary) (Hamilton et al., 1993), the

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[1] Maximal heterogeneity means that the model allows variation in all of the parameters across individuals and in the distribution function.

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Table 1
Regression results for the probability of being unemployed at t.
Source: Own calculations based on the ECHP, 1994–2001.

	Austria		France		Germany		Greece		Ireland	
Model	1	2	1	2	1	2	1	2	1	2
$\hat{\gamma}$	1.093 (0.198)	2.024 (0.459)	1.239 (0.127)	1.074 (0.198)	0.909 (0.121)	1.175 (0.239)	1.040 (0.107)	1.381 (0.181)	0.853 (0.155)	1.306 (0.437)
Lg-L	−654.8	−651.8	−1080.7	−1077.7	−1400.6	−1398.6	−1284.0	−1284.3	−747.9	−748.0
N	7035		9747		11158		9886		5441	
$\sigma^2_{\alpha_1}$	0.759 (0.260)	0.652 (0.261)	0.918 (0.222)	0.547 (0.211)	0.909 (0.197)	0.922 (0.217)	0.745 (0.157)	0.886 (0.216)	1.321 (0.357)	1.036 (0.605)
$\sigma^2_{\alpha_2}$		1.854 (0.914)		0.483 (0.341)		0.365 (0.261)		0.119 (0.139)		0.838 (0.876)
ρ_α		−0.641 (0.167)		0.488 (0.391)		−0.388 (0.243)		−0.904 (0.309)		−0.345 (0.212)

	Italy		Luxembourg		Portugal		Spain		UK	
Model	1	2	1	2	1	2	1	2	1	2
$\hat{\gamma}$	1.195 (0.070)	1.264 (0.121)	0.829 (0.326)	1.323 (0.533)	1.272 (0.116)	1.421 (0.227)	0.752 (0.066)	0.992 (0.115)	1.283 (0.166)	1.862 (0.285)
Lg-L	−2833.9	−2833.3	−322.0	−319.5	−1259.6	−1259.1	−3065.6	−3058.4	−738.0	−728.3
N	20063		6029		12745		13140		8332	
$\sigma^2_{\alpha_1}$	0.989 (0.133)	0.846 (0.144)	0.803 (0.477)	0.903 (0.432)	0.666 (0.150)	0.766 (0.189)	0.623 (0.087)	0.644 (0.101)	0.385 (0.168)	0.277 (0.177)
$\sigma^2_{\alpha_2}$		0.369 (0.220)		0.520 (0.579)		0.086 (0.142)		0.577 (0.165)		1.865 (0.627)
ρ_α		−0.041 (0.178)		−0.645 (0.236)		−0.473 (0.495)		−0.436 (0.116)		−0.748 (0.148)

Numbers in parentheses refer to standard errors. Model 1 refers to the standard RE probit model as in Eq. (1) and Model 2 to the heterogeneous slope model as in Eq. (2).

general economic situation (Kelvin and Jarrett, 1985) or options to compensate for the job loss (Jahoda, 1982) may relieve or intensify the threat. The aim of this paper is to assess the importance of individuals' heterogeneity related to previous unemployment experiences when measuring unemployment state dependence across Europe.

2. Data

Our analysis is based on the European Community Household Panel (ECHP), 1994–2001.[2] The sample consists of an unbalanced panel of prime aged men between the ages of 25 and 55. Women are excluded as it is difficult to predict the effect of career interruptions. Our results are based on the components from Austria, France, (West) Germany, Greece, Ireland, Italy, Luxembourg, Portugal, Spain and the United Kingdom. Our list of covariates includes age, marital status, number of children living in the household, educational level, year and region. The number of observations for each country is detailed in Table 1.

3. Econometric model

In the analysis, a standard random effects (RE) probit model and a RE probit that takes heterogeneity in the state dependence into account are estimated. The standard RE probit takes the following form:

$$y_{it} = 1\left(\gamma y_{it-1} + x'_{it}\beta + \varepsilon_i + u_{it} > 0\right) \tag{1}$$

with $y_{it} = 1$ if the individual i is unemployed at time t and 0 otherwise. The dependent variable is explained by its lagged outcome (y_{it-1}) and some explanatory variables x_{it}. To relax the assumptions that the heterogeneous intercept ε_i is uncorrelated with the explanatory variables and that the initial labor market positions are exogenous, the time mean of the explanatory variables ($\bar{x}$) and the initial labor market position (y_{i0})[3] are included with $\varepsilon_i = a_0 + \bar{x}'_i\pi + \theta y_{i0} + \alpha_{1i}$ and $\alpha_{1i} \sim N(0, \sigma^2_{\alpha_1})$. An idiosyncratic shock is accounted for which is assumed to be standard-normal distributed with $u_{it} \sim N(0, 1)$. Eq. (1) can be estimated by using Gaussian–Hermite quadrature (Butler and Moffitt, 1982).

In order to take heterogeneity in state dependence into account, we follow the suggestion by Stewart (2007) and include a second RE error term (α_{2i}) which is only considered if the individual was unemployed at $t-1$:

$$y_{it} = 1\left((\gamma + \alpha_{2i})y_{it-1} + x'_{it}\beta + \varepsilon_i + u_{it} > 0\right) \tag{2}$$

with $\varepsilon_i = a_0 + \bar{x}'_i\pi + \theta y_{i0} + \alpha_{1i}$ and $\alpha_{2i} \sim N(0, \sigma^2_{\alpha_2})$. While γ captures the *true* state dependence of unemployment, equal for each individual, α_{2i} corrects for the unobservable heterogeneity of unemployment experiences between individuals. As there might be an association between the general underlying individual-specific risk of experiencing unemployment and the effect of actually having experienced unemployment, a correlation between both random effects error terms is allowed, $Cov\ (\alpha_{1i}, \alpha_{2i}) = \rho_\alpha\sigma_{\alpha_1}\sigma_{\alpha_2}$. To estimate Eq. (2), Maximum Simulated Likelihood based on prime numbers, also called Halton draws, is applied (Train, 2009).

4. Results

Table 1 shows the estimation results for both estimators. Unsurprisingly, and regardless of the model chosen, the scarring

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2 Ideally, we would have worked with a more recent time period, but our analysis requires comparative data that follows individuals for a sufficiently long period of time (Arulampalam and Stewart, 2009) and, for example, in the *European Union — Statistics on Income and Living Conditions*, EU-SILC, individuals participate at maximum for four consecutive waves.

3 As the labor market position in the first observed period might not be randomly distributed, we follow Wooldridge (2005)'s suggestion to condition the estimation on the initial labor market position.

Table 2
Average partial effects for the probability of being unemployed at t (in percentage points).
Source: Own calculations based on the ECHP, 1994–2001.

Country	Model 1	Model 2	Ratio: Model 2/Model 1
Austria	0.082	0.282	3.427
	(0.037)	(0.122)	
France	0.107	0.146	1.371
	(0.032)	(0.042)	
Germany	0.077	0.108	1.412
	(0.023)	(0.039)	
Greece	0.097	0.118	1.218
	(0.025)	(0.036)	
Ireland	0.065	0.131	2.009
	(0.022)	(0.094)	
Italy	0.115	0.146	1.258
	(0.017)	(0.027)	
Luxembourg	0.031	0.048	1.565
	(0.026)	(0.046)	
Portugal	0.113	0.123	1.091
	(0.032)	(0.039)	
Spain	0.105	0.152	1.450
	(0.016)	(0.025)	
UK	0.115	0.282	2.450
	(0.052)	(0.083)	

Numbers in parentheses refer to standard errors.
Reading example: Referring to Germany in Model 1, on average the risk of being unemployed in the subsequent period is 7.7 percentage points higher for an individual who was unemployed in the previous period compared to someone employed.

effect of unemployment is found: being unemployed at $t-1$ increases greatly and significantly the risk of being unemployed in the subsequent period.[4] Moreover, indications are found in both models that the individuals also differ in their unobservables. Referring to Model 1 (the standard RE probit model), the variance of the random effects $\sigma^2_{\alpha_1}$ is significantly different from zero at the 10% level for each country. This can be also found in Model 2 (the heterogeneous slope model), with the only exception being for UK. In the case of $\sigma^2_{\alpha_2}$ in Model 2, the variance is significantly different from zero at the 10% level for the cases of Austria, Italy, Spain and UK.[5] Furthermore, for France, Germany, Ireland and Luxembourg the variance is above 0.3, though not significant at the 10% level. Looking at the correlation parameter ρ_α, except for the case of France, a negative correlation between the two random effects can be found, which is significantly different from zero at the 10% level for Austria, Greece, Luxembourg, Spain and UK.[6] A negative correlation indicates that for an individual who is less likely to become unemployed (because of higher skills and more motivation), the experience of unemployment has a greater negative impact on the likelihood of leaving the ranks of the unemployed compared to an identical individual who is more likely to become unemployed. This might indicate that individuals with a low unemployment risk evaluate their unemployment spells more negatively.

To facilitate the comparison between both models, and based on the estimation results, partial effects are derived for each observation:

$$PE_i = \Phi\left[\left(\hat{\gamma}_+\hat{\mu}\right)/\sqrt{\sigma^2_\upsilon}\right] - \Phi\left[\left(\hat{\mu}\right)/\sqrt{\sigma^2_\upsilon}\right] \quad (3)$$

with $\upsilon = \sigma^2_{\alpha_1} + \sigma^2_u$ in Model 1 and $\upsilon = \begin{cases} \sigma^2_{\alpha_1} + \sigma^2_u & \text{if } y_{it-1} = 0 \\ \sigma^2_{\alpha_1} + \sigma^2_{\alpha_2} + 2\rho_\alpha\sigma_{\alpha_1}\sigma_{\alpha_2} + \sigma^2_u & \text{if } y_{it-1} = 1 \end{cases}$ in Model 2 and $\hat{\mu} = x'_{it}\hat{\beta} + x'_i\hat{\pi} + \hat{\theta}y_{i0}$.[7,8] In Table 2, the average partial effect (APE) for each country is presented. In both models, the APE is significantly greater than zero at the 10% level, except for Luxembourg (Model 1 and Model 2) and Ireland (Model 2). As can be seen, the APE of past unemployment ranges between 6.5 (Ireland) and 11.5 (Italy and UK) in the standard RE probit model and between 10.8 (Germany) and 28.2 (Austria and UK) when accounting for heterogeneity in state dependence. If we compare the ratio for the APE between both models, the APE increases substantially, for example, for Germany (+41%), for Spain (+45%), for UK (+145%) and Austria (+242%).

5. Conclusions

Our results suggest that not only is there a considerable degree of state dependence in unemployment across Europe, but indications are also found for heterogeneity in unemployment experiences between individuals. Future research should take these results into account so as not to underestimate the scarring effect of unemployment.

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4 Note that due to different normalizations of the composite error term, the coefficient of the lagged dependent variable cannot be directly compared between both models (Arulampalam, 1999).

5 In the case of UK, Stewart (2007) finds comparable results with the BHPS but with smaller variances. However, it must be noted that, in his sample, individuals with consecutive unemployment spells are dropped. Furthermore, his analysis includes women, which might also have an impact on the variances.

6 For UK and Germany, the regressions were replicated with data from the BHPS and SOEP (respectively) for the time period 2000–2008 and comparable results were found.

7 We would like to thank an anonymous referee for making the formula explicit to us.

8 Note that the estimated intercept $\hat{a}_0$ is included in $\hat{\beta}$.