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TIME-DEPENDENT EFFECTS OF UNEMPLOYMENT BENEFITS*

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This paper presents methods to estimate the effects of time-dependent covariates in parametric duration models using microeconomic data. In the Finnish system persons who are eligible for the benefits have a risk to lose them after the first three months. In addition the earnings-related unemployment allowances decrease 20 per cent after the first 100 days unemployment. Using Finnish data it is shown that unemployment benefits have a negative effect on the probability of becoming employed during the first months, but after that period the effect vanishes. (JEL J64)

1. Introduction

In this paper the effects of unemployment insurance (UI) on spells of unemployment are examined. The circumstances of unemployed persons do not usually stay constant over time. Duration models based on the proportional hazards (PH) assumption imply constant effects of explanatory variables over time. The purpose of this paper is to estimate the time-dependent effects of time-dependent benefits on the re-employment probability during the unemployment spell. A technique for estimating these effects is presented using a Weibull model and Finnish microeconomic data. The aim of the paper is not to look only at the effect of changes in the replacement ratios over time, but also whether the impact of unemployment benefits on the re-employment probability varies with unemployment duration.

It is inevitable that econometric models do not include all the necessary explanatory variables either because they are unmeasurable or because their importance is unsuspected. The neglected heterogeneity may bias the parameter estimates towards zero. To correct for unobservable variables gamma and mass point heterogeneity across individuals are introduced into the model.

The paper is organized as follows. Section 2 introduces parametric duration models and time-dependent effects. Section 3 analyzes the effects of omitted variables and introduces gamma and mass point heterogeneity into the model. The results of the estimations are presented in section 4 and section 5 concludes the study.

2. Time-dependent effects of UI benefits

Before presenting the model with time-dependent covariates a generic form of the like-

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lihood function with the right censored duration data is presented. Consider independent pairs of independent random variables T and Z, where T is the duration variable of primary interest and Z is a censoring variable. A censoring time or a duration time are observed, $t = \min(T, Z)$, with an indicator for the complete spells c. If $T < Z$ then $c = 1$ and $c = 0$ otherwise.

Econometric duration models are specified in terms of the hazard function $h(t)$, which is the conditional probability that the person leaves unemployment at t given that he still is unemployed. The probability of being still unemployed until the duration t is given by the survivor function

$$(1) \qquad S(t) = e^{-I(t)},$$

where $I(t)$ is the integrated hazard

$$(2) \qquad I(t) = \int_0^t h(\tau)\, d\tau .$$

Using the rule of conditional probabilities, the unconditional probability (density function) that an individual leaves unemployment at t is a product of the hazard and survivor functions

$$(3) \qquad f(t) = h(t) e^{-I(t)} .$$

The likelihood contribution for an individual can then be written using the indicator for complete spells of unemployment c as follows

$$(4) \qquad \lambda = h(t)^{c} e^{-I(t)},$$

which is equal to $f(t)$ if $c = 1$ and $S(t)$ if $c = 0$.[1] The distribution of unemployment spells needs to be parametrized, and maximizing the likelihood function λ over the unknown parameters θ may be accomplished by maximizing a function $L(\theta) = \Sigma \log \lambda(\theta)$.

A commonly applied specification is the proportional hazards model, where the hazard function $h(t) = h_0(t)h_1(x)$ factors into the product of a function of duration time t, the baseline hazard, and function of the explanatory variables x. The Weibull model is a versatile family of duration distributions in view of its interpretation and its flexibility for empirical fit. Therefore it has been widely used in applications of duration models to unemployment spells.

In a Weibull model the baseline hazard can be parametrized as $h_0(t) = \alpha t^{\alpha-1}$, where α is the shape parameter. If $\alpha > 1$, the hazard function is increasing over the duration of the unemployment spell and it is said that there is *positive duration* dependence. If $\alpha = 1$, the hazard function is constant and the distribution of unemployment spells is exponential. If $\alpha < 1$, the hazard function is decreasing over time and it is said that there is *negative duration dependence*. The explanatory variables are introduced into the model in a log-linear form $h_1(x) = e^{x\beta}$. Consequently, the survivor, density and hazard functions of the Weibull distribution can be written as follows

$$(5) \qquad S(t) = e^{-t^{\alpha} e^{x\beta}}$$

$$(6) \qquad f(t) = \alpha t^{\alpha-1} e^{x\beta - t^{\alpha} e^{x\beta}}$$

$$(7) \qquad h(t) = \alpha t^{\alpha-1} e^{x\beta} .$$

To estimate the unknown parameters $\theta = (\alpha, \beta)$ the hazard function $h(t)$ and integrated hazard $I(t) = t^{\alpha} e^{x\beta}$ are substituted into the likelihood function, which is maximized with respect to the parameters.

Time-dependent effects

According to the Finnish UI system the circumstances of an unemployed person are different during the unemployment of the first three months. If there are no suitable jobs in the unemployed person's area of residence within the first three months of unemployment, the person does not have to accept an offer outside his area of residence. Also during the first months the unemployed person does not have to accept an offer, if the job is not suitable to him with respect to his education or previous work experience. This rule concerns persons who have education for their occupation and at least one year of job experience or alternatively persons who do not have proper education and at least two years experience in their job. A person who after being unemployed for three months does not accept an of-

[1] *To take the latent censoring variable explicitly into account the likelihood contribution* $\lambda = h_z^{1-c} S_z h^c S$, *where the subscript z is referring to the censoring variable. Since* $h_z^{1-c} S_z$ *involves no parameters of interest, one may proceed to estimate the model by maximizing a 'partial conditional likelihood' as given by the equation (4).*

fer loses his benefits unless he has not a good reason to reject it. Another change in the environment of an unemployed person is that the earnings-related unemployment allowances decrease 20 per cent after the first 100 days unemployment. If the effect of the time-dependent change is handled in a flexible manner, it should account for the higher hazard just after the first three months (see Kettunen, 1992a, 1993b). This is allowed for letting the unemployment benefits and their parameters vary over time.

The time trended variables may be replaced with their within spell average or using beginning of spell values (Heckman and Singer, 1984a). Usually in parametric models the variation in the explanatory variables across observations is used to take into account the time-dependent effects. The problem with these kinds of models is that the variation over time of the covariates may be absorbed by the baseline specification. Prentice and Gloeckler (1978) specify a semi-parametric model and use the variation in the mean of the covariates, i.e. the variation in the covariates across observations, to estimate the baseline hazard and structural parameters. No assumptions are made about the baseline hazard. In that sense the Prentice and Gloeckler approach is similar to Cox's partial likelihood technique (Cox, 1972, 1975). Their method has been proposed also by Han and Hausman (1986) and used by Moffitt (1985). Recently Meyer (1990) divided the duration of the unemployment into intervals of one week and extended the Prentice and Gloeckler model by using time-dependent covariates. One may suspect that estimating the baseline hazard with semiparametric methods may decrease the need to take the unobserved heterogeneity into account. A comparison of the parameter estimates of Cox's model and a Weibull model shows, however, that these models give rather similar results.

The PH model assumes that the effect of an explanatory variable is constant during the duration of the unemployment. An alternative is to assume that the effect varies with the duration, remaining constant within predefined intervals. Such an alternative may be relevant in long-term studies, and in cases where the environment of an individual changes starting at a known point in time it may even be the more natural model to apply.

Consider q intervals of duration time $(t_0, t_1], \ldots, (t_{q-1}, t_q]$ with $t_0 = 0$ and $t_q = \infty$. The hazard function of the Weibull model with time-dependent effects can be written as follows

$$(8) \qquad h(t) = \alpha t^{\alpha-1} e^{x(\beta+\mu_j)}, \quad \text{for } t_{j-1} < t \leq t_j,\ j = 1, \ldots, q,$$

where $\beta = (\beta_1 \ldots \beta_p)$ and $\mu_j = (\mu_{1j} \ldots \mu_{pj})$ are $1+q$ vectors of p parameters. By definition $\mu_j = 0$, as $j = 1$. One reason for this kind of specification of time-dependent effects is that the integrated hazard has a closed-form expression. The integrated hazard is obtained by integrating the hazard functions by intervals. That leads to the expression

$$(9) \qquad I(t) = \sum_{s=1}^{j-1} [I_s(t_s) - I_s(t_{s-1})] + [I_j(t) - I_j(t_{j-1})] .$$

In the Weibull case, e.g. in the third interval, it would be $I(t) = t_1^{\alpha} e^{x\beta} + (t_2^{\alpha} - t_1^{\alpha}) e^{x(\beta+\mu_2)} + (t^{\alpha} - t_2^{\alpha}) e^{x(\beta+\mu_3)}$. The likelihood contribution of an individual can be written as follows

$$(10) \qquad \lambda = \prod_{j=1}^{q} [h(t)^c e^{-I(t)}]^{d_j},$$

where d_j indicates the interval, i.e. $d_j = 1$ if $t_{j-1} < t \leq t_j$ otherwise $d_j = 0$.

The explanatory variables may be time-dependent as well, i.e. the time-dependent variables may take different values in the intervals. In this paper the interest concerning the PH assumption is in a single time-dependent explanatory variable, the benefit replacement ratio. Its effect is tested in two intervals $(t_0, t_1]$ and $(t_1, t_2]$, where $t_0 = 0$, $t_1 = 3$ and $t_2 = 24$ months. The longest spells of unemployment in the data are nearly two years. The economic reason for estimating the change of the hazard function is that after the first three months of unemployment the rules of the UI system and hence the behaviour of unemployed persons are different.[2] Thus, in our case $x(\beta + \mu_j)$ is

[2] *A more detailed analysis would be to divide the duration of unemployment into three intervals $(t_0, t_1]$, $(t_1, t_2]$ and (t_2, t_3), where $t_0 = 0$, $t_1 = 3$, $t_2 = 4.6$ and $t_3 = 24$ months. The second interval from 3 to 4.6 weeks (100 days of unemployment) would, however, be rather short for the investigation of the rules regarding labour mobility using parametric models of unemployment duration.*

written as $x\beta + x_{rj}(\beta_r + \mu_j)$, where x_{rj} are the benefit replacement ratios and $(\beta_r + \mu_j)$ are their parameters in the intervals. The rest of the explanatory variables x are constant over time.

The approach taken in this paper has several advantages. The method is more efficient than the earlier models by Prentice and Gloeckler (1978) and Meyer (1990) in the sense that the duration is continuous. It is not partitioned into intervals. The loss in efficiency is not necessarily dangerous. The parameter estimates may be sensitive with respect to how the duration is classified into days or weeks. The approach avoids inconsistent estimation of covariate coefficients due to allowing for the time-dependent covariates and their parameters to vary over time. In addition, unobserved heterogeneity across observations will be taken into account.

3. *The effects of omitted variables*

Gamma heterogeneity

The first approach in this section combines the correction for gamma heterogeneity and a parametric duration model with time-dependent covariates. The usual method for incorporating unobserved heterogeneity is to assume a parametric functional form for the pattern of heterogeneity. The gamma mixing distribution has been chosen, because it is analytically simple to use and it provides quite a flexible model for the distribution of the heterogeneity component. If unobserved characteristics are not adequately captured by explanatory variables, this may lead to biases in parameter estimates. Even if the omitted variables are uncorrelated with those which are included in the model, the parameters will be biased. It may be shown under fairly general conditions that the coefficients of explanatory variables are then biased towards zero (Lancaster and Nickell, 1980). Therefore, the parameters of the model may be expected to increase in absolute value when omitted variables are taken into account.

Suppose that the individuals in the sample differ to a certain degree with respect to some unobservable variable, say, motivation v. Each individual has his own v and hence his own hazard function h(t). Lancaster (1979) assumed that these hazards have a gamma distribution. The conditional hazard function in a Weibull model allowing for time-dependent effects and gamma heterogeneity is

$$(11) \quad h(t|v) = v\alpha t^{\alpha-1} e^{x(\beta+\mu_j)},$$

where v has a gamma density. The expected value of v is normalized to one and its variance σ^2 is estimated. The marginal survivor function, not conditional on v, is obtained by integrating over the assumed mixing distribution. The density function is obtained from the survivor function by differentiating and the hazard function is obtained as a ratio of the density and survivor functions. The hazard function allowing for gamma heterogeneity can be written as follows

$$(12) \quad h_g(t) = \alpha t^{\alpha-1} e^{x(\beta+\mu_j)} [1 + \sigma^2 I(t)]^{-1},$$

and the corresponding integrated hazard is

$$(13) \quad I_g(t) = (1/\sigma^2) \log [1 + \sigma^2 I(t)],$$

where I(t) is the integrated hazard of the original model (9). In our case $x\beta + x_{rj}(\beta_r + \mu_j)$ is substituted for $x(\beta + \mu_j)$, because we are interested in the time-dependent effects of a single time-dependent variable. The hazard function (12) and integrated hazard (13) are substituted into the likelihood function to estimate the unknown parameters.

Mass point heterogeneity

In this section a mass point approach to the incorporation of unobserved heterogeneity into duration models is described. Meyer (1990) found the computation of the discrete mixing distribution too difficult. In this context the computation can be done. The main method for incorporating heterogeneity has been to assume a parametric functional form for the pattern of heterogeneity. Heckman and Singer (1984a, b), who propose a discrete pattern of heterogeneity, have shown that estimates of the structural parameters may be sensitive with respect to the parametric forms assumed for heterogeneity. Furthermore, there is a limited number of tractable forms for mixing distributions available.

The approach dispensing with the need to specify a parametric distribution for the heterogeneity component has its origins in the work of Kiefer and Wolfowitz (1956), who showed

that a nonparametric characterization of the heterogeneity distribution ensures consistent estimation of simultaneously estimated structural parameters. Further work on the properties of mass point mixing distributions has been carried out by Simar (1976), Laird (1978), Lindsay (1983a, b) and Heckman and Singer (1984a, b). Applications of the mass point approach in the context of discrete choice models have been presented by Davies and Crouchley (1984), Dunn, Reader and Wrigley (1987), Davies (1987) and Card and Sullivan (1988). Applications to duration models have been presented by Brännäs (1986a, b), Trussell and Richards (1987) and Ham and Rea (1987).

The idea of mass point models is that the constant parameter of the basic model β_0 is partitioned into m location parameters u_k for each estimated group in the sample and each of the location parameters is given a probability p_k. In the case where m = 1, when there is one location parameter, the parameter u_1 is equal to the constant of the basic Weibull model β_0. Consequently, the likelihood function of mass point models reduces to the likelihood function of the basic Weibull model, and the model with one mass point and the basic Weibull model coincide.

In the case of parametric duration models the mixing likelihood for an individual can be written as follows

$$(14) \quad f_Q = \prod_{j=1}^{q} \left[\sum_{k=1}^{m} p_k h_k(t)^c e^{-I_k(t)} \right]^{d_j},$$

where $h_k(t) = \alpha t^{\alpha-1} e^{u_k + x(\beta + \mu_j)}$ and $I_k(t) = t^{\alpha} e^{u_k + x(\beta + \mu_j)}$ are the hazard function and integrated hazard for the group k in the Weibull case. In a model with one time-dependent explanatory variable $x\beta + x_{rj}(\beta_r + \mu_j)$ is substituted for $x(\beta + \mu_j)$.

To ensure that $p_k \in (0, 1)$ and $\Sigma p_k = 1$, the probabilities associated with each location have been defined using a multinominal logit type of formula

$$(15) \quad p_k = \frac{e^{g_k}}{1 + \sum_{l=1}^{m-1} e^{g_l}}, \quad k = 1, \ldots, m-1,$$

where g_k, k = 1, ..., m – 1, are parameters to be estimated. The probability of the last mass point $p_m = 1 - p_1 - p_2 - \ldots - p_{m-1}$. By definition $p_1 = 1$ when m = 1. The standard errors of the probabilities p_k can be approximated by the well known delta method.[3]

The procedure of estimating a discrete mixing distribution is to increase the number of points of support until the Gateaux derivative of the log likelihood function turns negative. Then the procedure is stopped and the semiparametric ML estimator is obtained.[4]

4. The results

Data on 2077 Finnish unemployed persons was collected for this study from various registers. The data set is more reliable than the data sets based on interviews. In order to guarantee that the sample would be randomly generated and seasonally representative, every hundredth individual was picked from the flow into unemployment during the year 1985.

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[3] *The first order Taylor series expansion gives*

$$p_k(\hat{g}) = p_k(g) + (\hat{g} - g)' \frac{\partial p_k}{\partial g},$$

where $g = (g_1 \ldots g_{m-1})$. *The variance can then be approximated by*

$$Var[p_k(\hat{g})] = \frac{\partial \hat{p}'_k}{\partial g} \; Var(\hat{g}) \frac{\partial \hat{p}_k}{\partial g}.$$

[4] *The objective is to estimate the discrete mixing distribution Q consistently with the atomic densities, a maximizer of the mixture likelihood function* $\gamma(Q) = \pi f_Q$. *Maximizing the likelihood function* $\gamma(Q)$ *over Q may be accomplished by maximizing the log likelihood function* $L(f) = \Sigma \log f_Q$. *Following Lindsay (1983a) and Heckman (1984b) it can be seen that* $L(f) = \Sigma \log f_Q$ *is differentiable. The Gateaux derivative of the functional L is taken at* L_{Q_k} *with k mass points towards* $L_{Q_{k+1}}$

$$D(u; Q) = \lim_{p \to 0} \{L[(1-p)f_{Q_k} + p f_{Q_{k+1}}] - L(f_{Q_k})\}/p$$

$$= \Sigma [(f_{Q_{k+1}} - f_{Q_k})/f_{Q_k}]$$

$$= \Sigma f_{Q_{k+1}}/f_{Q_k} - n,$$

where it will be understood that the summing is over observations. This procedure is suggested also by Brännäs and Rosenqvist (1988) in the context of count data models. Maximum likelihood algorithms are directly applicable to the constrained problem of maximization over discrete mixtures Q with a fixed number of support points. The Berndt, Hall, Hall and Hausman (1974) algorithm is used to estimate the unknown parameters. A simple first order check for a global maximum is to verify that $D''(u^*; Q) \leq 0$ *at the support points of measure Q.*

The sample was taken from the unemployment register of the Ministry of Labour. The individuals were then followed until the end of their unemployment periods, but at most until the end of 1986. The income and asset information was compiled into the data from the tax register. The information on unemployment benefits was compiled from the registers of the bank Postipankki and the Social Insurance Institution. In the original sample from the flow into unemployment 29 per cent of the workers received the basic unemployment allowance, 29 per cent received the earnings-related unemployment allowance and 42 per cent did not receive any form of benefits. About 40 per cent of the observations are right censored, i.e. the complete spells of unemployment are not observed. The data on unemployment durations and the Finnish UI system have been described and studied more extensively by Kettunen (1991a, b, 1993a, b, 1994). The data appendix includes the description of the variables used in the study.

The results of the estimations are presented in Table 1. The first model is the basic Weibull model with the hazard function (7), where an average replacement ratio over the unemployment period is used. The second model includes the time-dependent replacement ratios in the two intervals, $(t_0, t_1]$ and $(t_1, t_2]$, where $t_0 = 0$, $t_1 = 3$ and $t_2 = 24$ months. During the first three months about 36 per cent of the unemployed persons became employed and 10 per cent were censored. In the model $x\beta$ is replaced by $x\beta + x_{rj}\beta_r$. The second column of Table 1 presents this model. The negative effect of the replacement ratio β_r decreases substantially when the time-dependent replacement ratios are introduced into the model.

A Weibull model with time-dependent effects is in the third column. In that model $x\beta$ is replaced by $x\beta + x_{rj}(\beta_r + \mu_2)$. The parameter estimate β_r takes a value –0.894, and after the first three months the additional parameter estimate μ_2 takes a positive value 0.871. Unemployed persons who are eligible for benefits face a risk of losing benefits after the first three months. The effect of risk increases the re-employment probability and it is captured by the parameter μ_2. The result is in concordance with the semi-parametric evidence that the re-employment probability increases strongly at the three months of unemployment in Finland (see Kettunen, 1993b). Unfortunately there is no information on the disqualifications in the data.

The PH assumption is not valid either after allowing for gamma heterogeneity in the fourth model, since the corresponding parameter estimates of the replacement ratio take the values –1.506 and 1.475. It is interesting to note that Nickell (1979) using the data from the UK and a different kind of model found similar effects of UI benefits. In both of the studies the effect is first negative and statistically significant but later on the effect vanishes.

The results of estimations of mass point models are in Table 2. The model with two mass points produces approximately constant hazard functions for the two groups which are not controlled for explanatory variables. The models with three or four mass points produce increasing hazard functions. An increasing hazard function is in concordance with standard search theories with a limited search horizon. Even though the hazard functions of the groups are monotonically increasing in the final model the sample hazard is not necessarily monotonous. The sample hazard is derived by Kettunen (1993c) and it is found to be

$$(16) \quad h(t) = \sum_{k=1}^{m} p_k h_k(t) e^{-I_k(t)} \Big/ \sum_{k=1}^{m} p_k e^{-I_k(t)} .$$

Figure 1 illustrates the sample hazard for an average person in the sample. It can be seen that the hazard is rather flexible and it makes a prominent jump at the three months unemployment, where the eligibility rules become stricter.

The absolute values of statistically significant parameter estimates increase in most cases when more mass points are introduced into the model, as is to be expected. Lindsay's (1983a) criterion was used to decide the number of mass points. The values of the Gateaux derivative of the models with 2, 3 and 4 mass points are 1.34, 9.12, and –3.63 respectively, showing that four mass points are enough to rectify the effect of omitted variables in this data set.

The full specification testing of the estimated models are excluded from this article, since there is limited space available. The generalized residuals of the mixture models are derived in Kettunen (1990), where the residuals are examined whether they have a unit exponential distribution. The Weibull model al-

Table 1. Time-dependent effects of UI benefits allowing for gamma heterogeneity.

	(1)	(2)	(3)	(4)
		Std. errors in parentheses		
Shape parameter	0.861	0.853	0.822	1.096
	(0.020)	(0.021)	(0.022)	(0.054)
Variance of heterogeneity				0.955
				(0.161)
Constant	–1.478	–1.576	–1.454	–1.183
	(0.136)	(0.137)	(0.139)	(0.207)
Number of children	–0.004	–0.088	–0.082	–0.134
	(0.050)	(0.050)	(0.049)	(0.074)
Married, 1 = yes	0.170	0.207	0.203	0.198
	(0.065)	(0.066)	(0.065)	(0.099)
Sex, 1 = male	–0.007	–0.040	–0.041	–0.074
	(0.056)	(0.057)	(0.057)	(0.088)
Age, years	–0.042	–0.044	–0.044	–0.060
	(0.003)	(0.003)	(0.003)	(0.005)
Level of education	0.064	0.053	0.066	0.029
	(0.058)	(0.059)	(0.059)	(0.093)
Training for employment	0.176	0.187	0.181	0.331
	(0.072)	(0.074)	(0.073)	(0.116)
Member of UI fund	0.213	0.243	0.237	0.356
	(0.060)	(0.062)	(0.061)	(0.093)
Came from schooling	0.291	0.299	0.291	0.380
	(0.078)	(0.079)	(0.078)	(0.128)
Came from house work	–0.711	–0.716	–0.731	–0.895
	(0.124)	(0.125)	(0.124)	(0.171)
Regional demand	0.168	0.308	0.271	0.487
	(0.238)	(0.240)	(0.240)	(0.330)
Occupational demand	0.641	0.743	0.715	0.457
	(0.600)	(0.609)	(0.602)	(0.943)
Taxable assets	1.021	1.997	1.224	1.223
	(1.080)	(1.102)	(1.073)	(1.393)
Replacement ratio, β_r	–1.223	–0.376	–0.894	–1.506
	(0.150)	(0.120)	(0.191)	(0.264)
Replacement ratio, μ_2			0.871	1.475
			(0.208)	(0.267)
Log likelihood	–4962.5	–4993.4	–4985.4	–4950.4

lowing for gamma mixing distribution seems to be slightly better specified than the basic Weibull model. The Weibull model allowing for the discrete mixing distribution seems to be well specified. The information matrix and likelihood ratio tests confirm the conclusions based on the graphical method.

Many of the explanatory variables have significant effects on the re-employment probability. Unemployed persons who have children or persons who are not married have lower probabilities. Age is a very significant factor. Old people are more apt to incur problems in finding jobs. Training for further employment has a significant and positive effect on the re-employment probability. Members of the UI funds, i.e. members of the Finnish labour unions, are often skilled workers and therefore they become employed earlier than the non-members. The persons leaving school or the army usually have no great problems. They leave unemployment clearly earlier than the others. The persons who have come from house work find it very difficult to find acceptable job offers.

In the model with four mass points the parameter estimate of the replacement ratio takes a value of –1.890 and the additional parameter μ_2 due to the risk of losing benefits takes a value of 1.752. The negative effect of the replacement ratio vanishes after the first three months and the PH assumption is not valid.

Table 2. Time-dependent effects of UI benefits allowing for mass point heterogeneity.

	Number of mass points		
	m = 2	m = 3	m = 4
	Std. errors in parentheses		
Shape parameter	0.987	1.194	1.288
	(0.040)	(0.064)	(0.091)
Number of children	–0.109	–0.175	–0.184
	(0.065)	(0.079)	(0.089)
Married, 1 = yes	0.201	0.216	0.199
	(0.087)	(0.103)	(0.115)
Sex, 1 = male	–0.060	–0.088	0.085
	(0.077)	(0.092)	(0.104)
Age, years	–0.055	–0.063	–0.069
	(0.004)	(0.006)	(0.007)
Level of education	0.029	0.066	0.040
	(0.080)	(0.098)	(0.109)
Training for employment	0.331	0.240	0.296
	(0.102)	(0.118)	(0.132)
Member of UI fund	0.333	0.368	0.411
	(0.083)	(0.097)	(0.110)
Came from schooling	0.341	0.408	0.441
	(0.110)	(0.131)	(0.148)
Came from house work	–0.819	–1.011	–1.114
	(0.153)	(0.187)	(0.206)
Regional demand	0.440	0.420	0.489
	(0.297)	(0.350)	(0.388)
Occupational demand	0.609	0.451	0.512
	(0.826)	(0.980)	(1.106)
Taxable assets	0.881	2.087	1.369
	(1.255)	(1.594)	(1.621)
Replacement ratio, β_r	–1.276	–1.741	–1.890
	(0.229)	(0.303)	(0.345)
Replacement ratio, μ_2	1.302	1.644	1.752
	(0.244)	(0.297)	(0.327)
u_1	–0.980	–0.004	0.459
	(0.193)	(0.247)	(0.366)
u_2	–2.738	–2.103	–1.360
	(0.238)	(0.259)	(0.478)
u_3		–4.865	–2.792
		(0.816)	(0.489)
u_4			–7.277
			(7.803)
p_1	0.648	0.272	0.187
	0.060)	(0.014)	(0.009)
p_2	0.352	0.617	0.345
	(0.060)	(0.023)	(0.052)
p_3		0.112	0.399
		(0.037)	(0.016)
p_4			0.069
			(0.027)
Log likelihood	–4956.5	–4945.9	–4943.6

The key parameter estimates are presented in elasticity form, since only then one is able to see how important the effects are. The elasticity of the re-employment probability

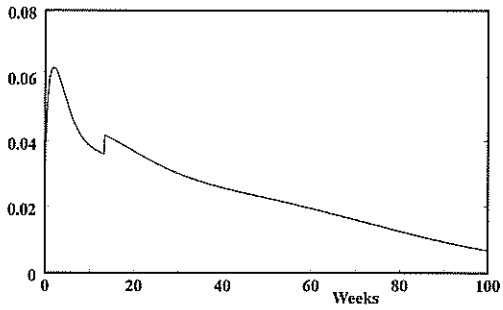

Figure 1. The sample hazard function of a Weibull mass point model

with respect of the average replacement ratio is –0.21 in the basic Weibull model. This specification is, however, rather restrictive, since it does not allow the elasticity to change over the intervals. The elasticities for the first three months are after that period allowing for discrete mixing distribution are –0.28 and –0.03, respectively.

5. *Concluding remarks*

In this paper the effects of unemployment benefits on the unemployment spells were examined. In the Finnish system the circumstances of an unemployed person change starting at a known time point. In this paper it was allowed for the effects of unemployment benefits to vary with the duration of unemployment spell, remaining constant within predefined intervals. A technique for estimating the time-dependent effects of time-dependent explanatory variables on the re-employment probability was presented.

If the average replacement ratio during the unemployment spell is used, the effect of the replacement ratio on the re-employment probability is negative. The microeconomic data collected from various registers include, however, the time-dependent replacement ratios. Alternative models with time-dependent effects of unemployment benefits were estimated. The replacement ratio has a negative effect on the re-employment probability during the first three months, but after that period the effect vanishes.

Even though the data are rich of explanatory variables and more reliable than the data from surveys, there is reason to assume that relevant

variables have been omitted from the model. The influence of omitted variables was taken into account in estimation assuming that the effects have a gamma and discrete mass point distribution. When heterogeneity is introduced into the model the absolute values of parameter estimates increase, but the correction for omitted variables does not eliminate the result that the effect of UI benefits vanishes after the first three months.

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Data appendix

Variables of the data

Duration of unemployment is calculated in weeks and it is the difference between the date of entry into unemployment and the date of returning to work. The data includes also other forms of exit than becoming employed. These are called censored observations. Mean = 15.06.

Number of children is the number of unemployed person's children who are younger than 18 years. Mean = 0.23.

Married is a dummy variable, 1 = yes. Mean = 0.37.

Sex is dummy variable, 1 = male. Mean = 0.54.

Age is measured in years. Mean = 31.2.

Level of education is a dummy variable, 1 = at least 12 years of education. The level of education is based on the education code of the Central Statistical Office of Finland. Mean = 0,45.

Training for employment is a dummy variable, 1 = The person has got training for further employment. Training for employment is course participation, which has been occurred before the unemployment, but not necessarily immediately before it. Mean = 0.15.

Member of UI fund is a dummy variable, 1 = yes. Mean = 0.42.

Came from schooling is a dummy variable, 1 = The person has come from schooling or from the military service. Mean = 0.13.

Came from house work is a dummy variable, 1 = The person has come from house work or elsewhere outside the labour force. Mean = 0.07.

Regional demand describes the regional rate of jobs available. It is the number of vacancies divided by the number of job seekers in the area. Mean = 0.10.

Occupational demand describes the occupational rate of jobs available in the whole country. It is the number of vacancies divided by the number of job seekers in the occupation group. Mean = 0.12.

Taxable assets has been compiled from the tax register and it is measured in millions of marks. Mean = 0.011.

Replacement ratios in the intervals, 1–3 and 3–24 months are unemployed person's average replacement ratios after tax in those intervals. Average weekly unemployment benefits after tax have been divided by the average weekly income in 1985 after tax. The means of the replacement ratios are 0.29 and 0.55 for the persons receiving earnings-related unemployment allowance and 0.26 and 0.41 for the persons receiving the basic unemployment allowance. The average replacement ratios are lower during the first three months, since no benefits are paid during the qualifying waiting period of benefits. Also reductions and disqualifications of benefits decrease the average replacement ratios. Some persons do not even apply for the benefits.