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Duration Dependence in Unemployment Insurance and Social Assistance: Consequences of Profiling for the Unemployed

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1 Introduction

It is well-known that the probability of an unemployed person finding a job decreases over the unemployed spell (e.g. Abbring (1997) and van Andel (1995)). For the Dutch labour market, this so-called 'negative duration dependence' has been confirmed for recipients of both unemployment insurance (UI), and social assistance (SA) benefits.[1] Various mechanisms may account for the existence of negative duration dependence. Unemployed job seekers may become discouraged, and consequently search less intensively for jobs. They may also lose their knowledge and working skills, and or become stigmatised by potential employers. All these phenomena result in duration dependence at the individual level. However, even if individual exit rates do not vary with duration, the aggregation over job seekers leads to duration dependence if there is variation in the exit rates between individuals. This is because the unemployed with low exit probabilities will tend to cluster into long-term unemployment. It is not easy to distinguish between individual and sorting effects, as they exert similar effects on the aggregate probability of finding a job. The distinction is not only a statistical, but also a policy issue — in particular with respect to policies that target the unemployed with bad job prospects.

In The Netherlands, local public employment services use profiling techniques to determine the individual prospects of finding a job. In principle, profiling occurs at the moment of entry in UI or SA. Unemployed are assigned to four possible 'phases'; the higher a phase, the lower the prospects on work. Each phase comes with its own special policy instruments. This approach bears two possible risks. First, it is questionable whether observed, administrative characteristics of the unemployed are sufficient to estimate accurate profiling measures. Second, individual duration dependence may be far more important than sorting effects. In that case, more general policy measures would be more effective in diminishing unemployment.

Over the years, a broad literature has evolved in with different methods for analysing this question. At the same time, databases have become available that allow for micro-

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[1] There is only one exception to this: UI-beneficiaries are more likely to find jobs near the end of the period of entitlement; hereafter, the unemployed are faced with a decrease in their income as they flow into the SA (see, e.g., Lindeboom and Theeuwes, 1993).

economic analyses, where a distinction is made between sorting and individual effects. In this paper, we use the Income Panel Research (IPR) database, which consists of a sample of individual records collected by Dutch tax authorities. This data set allows us to follow individuals over a long period of time, both in the SA and UI benefit programmes. With this information, we estimate duration models[2] to assess the accuracy of profiling for UI and SA beneficiaries. In particular, our analysis addresses the question which part of the duration dependence effect can be attributed to the individual effects, and which part to 'indirect' sorting effects.

Our analysis suggests that after an unemployment spell of half a year, the decrease in the job finding rate for SA recipients can be attributed for 20 to 25% to sorting effects that are caused by observed differences in individual characteristics. After a three- to four-year period, the probability of finding a job deteriorates further, but only because of individual duration effects. This means that the sorting mechanism has ended. For UI recipients, the decrease in the job finding rate can also be attributed for 25% to the (same) sorting effects. After a three- to four-year period in the UI programme, the job finding rate deteriorates further only as a result of individual duration effects.

All in all, sorting effects explained by the observed individual characteristics affect the job finding rate only in a limited way. The use of additional information (describing part of the heterogeneity that is unobserved in the current analysis), for example on the motivation of the unemployed, may improve the accuracy of profiling techniques. Still, our results indicate that the individual duration effects are more important. As a result, targeting specific groups (at the moment of inflow into unemploment) alone bears a great risk of long term unemployment for those unemployed that are (initially) classified as having good job prospects. Therefore, the profiling techniques require a supplementary policy to reduce long-term unemployment, e.g. by active counseling and monitoring all unemployed after a certain period of time.

The structure of the paper is as follows. Section 2 sheds light on the factors that determine the probability that a SA beneficiary or a unemployment beneficiary finds a job. Section 3 briefly describes the estimated duration model. Section 4 describes the IPR data, after which section 5 presents the results of the estimated model. Finally, section 6 draws some conclusions.

[2] In our analysis, we estimate reduced form models. For an example of a structural model approach where the empirical duration model is derived from theoretical arguments, we refer to Van den Berg (1990).

2 Factors determining the probability of finding a job

Various theories attempt to explain the job prospects of unemployed job seekers (for a complete survey, see Jehoel-Gijsbers (1993)). In this section, we briefly explain the theory that most commonly serves as a benchmark for analysis, job search theory. For a complete (and more formal) treatment of this theory we refer to Mortensen (1985).

In job search theory explicit account is taken of the presence of search frictions on the labour market. Finding a job therefore takes time. The duration of the search process is determined by the probability of a job offer and the probability that a job offer is accepted. Various characteristics may influence these two probabilities. Apart from personal characteristics (like age and gender), one might also think of the level of the reservation wage, (former) wage earnings, and the intensity of the search. In general, a high reservation wage results in a long spell of benefits. However, if individuals search rather intensively, this behaviour shortens the expected duration of the spell. Job search theory mainly addresses the behaviour of unemployed job seekers. More recently, attention has been focused on employees and employers. Job search theory can also be used as a benchmark for an analysis of education and training. Investments in education and training increase the human capital of workers, thus increasing the viability of a match between employers and employees.

All in all, the job finding rate may be influenced by various variables.[3] Possible variables may include:

(1) Age: The closer a person approaches the age of retirement, the shorter gets the remaining time horizon, and thus the less attractive it becomes to search for a job. The advantages of the new job are difficult to explore in a short period, both for a worker and and employer.

(2) Work experience: In general, the productivity of an employee increases with work experience. High productivity - if not firm specific - increases the surplus of matches with employers. This increases the probability of finding work.

(3) Education: Education is correlated with the productivity of an individual. Therefore, in analogoy to work experience, skilled job seekers are more attractive for employers.

(4) The elapsed spell of unemployment: The unemployed lose part of their knowledge and worker skills while under a benefits programme. Therefore, the length of the unemployment spell can have a negative effect on the job finding rate.

[3]Here, we refer to Devine and Kiefer (1991) for a survey on empirical search models.

(5) The reservation wage: According to job search theory, the level of the reservation wage reflects the willingness to accept a job offer. The reservation wage strongly depends on the value attached to leisure, as well as the replacement rate. Further, raising children may explain the value that is attached to household activities. Due to traditional role models, this value may vary between men and women.

(6) Costs and restrictions of the job search process: Generally, high search costs shorten the search period for a job. Examples are those costs incurred to find a job (advertisements, newspapers), and opportunity costs like the loss of income while being on benefits. Further, liquidity constraints may influence the length of the search period. In contrast to this, credits and partner income may result in a longer search period.

3 The model

Data on individual duration spells are needed to obtain information on duration effects. In our analysis, a distinction can be made between completed and ongoing spells. Both types of spells can be used to estimate duration or hazard rate models. The hazard rate is defined as the rate at which unemployed leave unemployment within a short period of time, given that one has been unemployed until that moment. In our model, the hazard is into two possible, 'competing risks', that into work and to other destinations. A large part of the outflow out of benefits, in particular that of SA benefits, consists of transitions into other destinations than finding a job. It is likely that both risks are correlated. For example, individuals that have a partner with an income may have a high probability of becoming nonparticipant, and a low probability of finding work. By using a competing risks structure, we try to take into account correlation.[4]

For a survey on the econometric analysis of duration models we refer to Lancaster (1990). In modeling duration effects, a distinction can be made between parametric and nonparametric models. In the first case, the pattern of duration dependence is restricted to have a particular functional form, for example a Weibull-distribution; the hazard rate then increases or decreases monotonically over time. This method has the advantage that the estimated parameter(s) have a clear, unambiguous interpretation. In case of the Weibull-distribution, there is only one parameter that describes the pattern of duration dependence. As an alternative, the pattern of duration dependence can be estimated nonparametrically. Here, the idea is that imposing a minimum of (functional form) restrictions results in minimizing the risk of misspecification. Mostly, the hazard rate

[4] As an alternative to this, spells ending in other destinations than work could be treated as incomplete ('censoring'). However, given the correlation between the outflow to work and to other destinations, the result may be that censoring is not random, resulting in estimation biases.

then is specified as a ‘piece-wise constant’: for a number of consecutive time intervals, the hazard is allowed to vary. We choose for this specification, as it allows to mimic the non-monotonous pattern of duration dependence in the data.

Unobservable heterogeneity

Various factors influence the hazard into work. Some are observed with the data at hand, whereas (most) others are not. For instance, the motivation of an unemployed person, for which the IPR database has no information, has a positive effect on the hazard to work. As mentioned before, differences in individual hazard rates result in a negative duration dependence, observed at an aggregated level. Ideally, one would like to observe all factors that determine these individual differences, in order to correct for them so that unbiased duration dependence remains. However, this situation will not occur when less than all factors are observed. In practice at least some unobservable heterogeneity will remain.

Unobservable heterogeneity can be taken into account in various ways. First, in analogy to other types of regression, one can model the unexplained part of a dependent variable as an error term. Some assumptions are needed with respect to the functional form of these errors terms (for example, by adopting a log-normal distribution). By extending the model in this way, we are able to measure the effect of unobservable heterogeneity on duration dependence. A disadvantage of this method is that the outcome of the estimation may be influenced by the (arbitrarily) chosen distribution of the error term. Therefore, a more flexible nonparametric method may serve as an alternative, for example by dividing the total group of the unemployed into two (or more) subgroups with different levels of unobservable effects. Then, for both (or more) groups the concerning weights are estimated, as well as the impact of unobserved differences on the hazard (Heckman and Singer (1984)).

4 The data

Introduction

The IPR (Income Panel Research) database consists of a sample of about 75,000 individual observations, collected by tax authorities over the period 1989-1996. A number of possible states is distinguished, depending on the individual income status (SA benefit, UI benefit, wage-income, no income, disability benefit, etc..) For our analysis, we use 6307 individual observations of SA beneficiaries and 11,465 cases of

UI beneficiaries. These observations are measured at the moment of entry in these programmes (as from 1989). For each individual, we observe a complete or incomplete unemployment spell, together with various individual characteristics.

A number of spells in the IPR database are exactly equal to one year, or a multiple of this. Probably in almost all cases these spells last *at most* one year (or a multiple of this.). Therefore, we make this assumption in the estimation of the model. Table 1 shows that the subset of these cases does not strongly differ from the total sample of SA and UI beneficiaries. This group is only lower educated, older and consists of relatively many unemployed that have a partner with an income. Possibly, these compositionary differences, together with the assumption that the subset of observations is assumed to last at most one year (or a multiple) may bias our estimation results. We tested for this by estimating the model without imposing this assumption. This did not change our results significantly, and in particular not the results with regard to the pattern of duration dependence.

Table 1 *Total sample, compared to the subset with spells expressed in years only*.

	SA-beneficiaries				UI-beneficiaries			
	Subset (N=1092)		Total sample (N=6307)		Subset (N=432)		Total sample (N=11465)	
	average fraction	st.dev.	average fraction	st.dev	average fraction	st.dev	average fraction	st.dev
Female	0.55	0.015	0.52	0.0063	0.41	0.019	0.40	0.0046
Partner with income	0.38	0.015	0.30	0.0058	0.51	0.047	0.40	0.0047
Child support	0.25	0.013	0.28	0.0057	0.28	0.022	0.28	0.0042
Higher education	0.044	0.0064	0.18	0.0023	0.0070	0.0040	0.0055	0.0021
Disabled	0.021	0.0042	0.029	0.0021	0.13	0.016	0.060	0.0022
Age (in years)	36.0	0.41	30.4	0.14	41.0	0.64	33.2	0.11

Comparing the Income Panel Research database with SA statistics

A comparison of the data from the IPR database with more generally used data of SA authorities (obtained from local authorities) shows that short spells are observed less often in the IPR (see table 2). A possible explanation for this is with respect to the registration of short term unemployed that enter into benefit programmes repeatedly. In the IPR these people are counted only once, in contrast to the other statistics. Table 3 reveals that the age and gender distribution are more or less the same in both databases.

Table 2 *Comparison of Social Assistance in IPR database with statistics of the Social Assistance Authorities, stock at end of year 1995 ; duration and gender distribution*

	Official SA statistics		IPR database	
	men	women	men	women
Duration in years	%			
< ½	18	14	13	9
½ - 1	12	10	16	14
1 - 2	19	16	15	15
2 - 3	12	12	11	11
3 - 4	8	8	7	8
4 - 5	5	6	6	8
> 5	26	34	31	35
Total number (x 1000)	246	334	235	345

Table 3 *Comparison of the Social assistance in IPR with statistics of the Social Assistance Authorities (SAA), stock at end of year 1995 ; age- and gender distribution*

	Total		Men		Women	
	SAA	IPR	SAA	IPR	SAA	IPR
Age	%					
18-24	12	13	12	13	12	13
25-34	34	34	37	38	32	32
35-44	25	25	24	22	26	27
45-54	18	17	16	16	19	17
55-65	11	11	11	11	12	11
total number (x1000)	580	581	246	235	334	345

Comparing the IPR database with the NISI database

Apart from the IPR database of Statistics Netherlands, the National Institution for Social Insurance (NISI) administers data of UI beneficiaries. Table 4 compares the distribution of complete spells according to the IPR and the NISI-data. Just like in table 1, we find that short spells are under reported in the IPR database. Again, this is due to the way of registration in the IPR.

Table 4 *Comparison of Spells of Ended UI Benefits in IPR*[a] *database with the National Institution for Social Insurance (NISI) database end of 1995*

	NISI	IPR
Duration in years	%	
<½	60	45
½ - 1	14	40
1 - 2	16	10
2 - 3	6	4
3 - 4	2	1
4 - 5	1	1
>5	1	0
Total(numbers in thousands)	590	714

[a] For a number of IPR observations the length of the spell is not known. The listed percentages are calculated on the basis of spells of which the length is known.

Operationalization of the model

Given the IPR, the following variables are used in the empirical analysis:

(1) Age at time of moment of entry of the benefit
(2) Education. This (proxy) dummy variable indicates whether a person has received a scholarship for university education.
(3) Receiving child support, or not.
(4) Having a partner who earns income, or not.

(5) Gender.

(6) A ‘health-dummy’. This dummy indicates whether person has received disability benefits in the past. Here, it should be mentioned that not all the disability beneficiaries in the IPR database can be properly identified.

(7) Duration of the spell. These are completed spells in the SA or UI programmes.

In chosing these variables, we are aware that this list probably contains incomplete information on the factors determining the hazard into work. However, our model allows us to assess the explanatory power of administrative information that is used mostly for profiling.

5 Estimation results

As mentioned before, the aggregation over individual job seekers leads to overestimation of duration dependence. To what extent is this the case in the IPR-data? In equation 1 we estimate a duration model for SA recipients without using any explanatory variables, apart from the spells lengths (see first column of table 5). Equation 3 of table 6 does the same for the UI recipients. Thus, for both equations the duration effects are not corrected for any differences in individual characteristics. The estimation results for these equations show a pattern of duration dependence that follows from individual duration dependence, together with that from sorting effects. In equations 2 and 4 we add a number of explanatory variables (like gender and age). This results in a less steep pattern of negative duration dependence; differences in the observed individual characteristics lead to sorting effects. The differences in duration dependence between the two equations (1 and 3, respectively, with 2 and 4) indicate the size of these (measurable) sorting effects.

The first columns of table 5 and table 6 indicate that duration dependence for both the SA and the UI benefits is more prominent with respect to the hazard to work than that to other destinations. The hazard to work strongly diminishes already in the first two years. The pattern of negative dependence with respect to the hazard to other destinations reasons differs between the SA and UI benefits programmes: in contrast to the SA, additional negative duration dependence effects end after around three years for UI.

Generally, the coefficients in equations 2 and 4 have the expected signs. For instance, we find that women find a job less quickly than men. Also, for SA benefit programmes we find a negative impact of partner income, or raises and child support. Unemployed

Table 5 Analysing the sorting effect: comparing equations 1 and 2 (Social Assistance)

	Equation 1		Equation 2		Difference	
Number of observations	6307		6307			
Log-likelihood	− 19419.3		− 18902.1			
Hazard to work	coefficient	std. error	coefficient	std. error	coefficient	std. error
Constant	− 2.70	0.025	− 2.29	0.044		
Woman			− 0.26	0.043		
Working Partner			− 0.14	0.056		
Child support			− 0.48	0.062		
Highly educated			0.59	0.051		
Disabled			− 1.16	0.28		
age 25-35 years			− 0.42	0.053		
age 35-45 years			− 0.64	0.084		
age 45-65 years			− 1.55	0.12		
6-12 months spell	− 0.74	0.060	− 0.58	0.060	0.16	0.085
12-24 months spell	− 1.46	0.074	− 1.17	0.074	0.29	0.10
24-36 months spell	− 1.84	0.11	− 1.46	0.11	0.37	0.16
36-48 months spell	− 2.50	0.20	− 2.02	0.20	0.48	0.28
>48 months spell	− 3.44	0.28	− 2.95	0.28	0.49	0.40
Hazard to other						
Constant	− 3.01	0.03	− 2.96	0.051		
Woman			− 0.0021	0.042		
Working Partner			0.30	0.044		
Child support			− 0.12	0.046		
Highly educated			− 0.020	0.072		
Disabled			0.21	0.096		
age 25-35 years			− 0.15	0.053		
age 35-45 years			− 0.14	0.064		
age 45-65 years			− 0.20	0.065		
6-12 months spell	− 0.060	0.054	− 0.026	0.055	0.034	0.077
12-24 months spell	− 0.68	0.063	− 0.66	0.063	0.020	0.089
24-36 months spell	− 0.82	0.084	− 0.81	0.085	0.018	0.12
36-48 months spell	− 0.99	0.11	− 0.98	0.11	0.017	0.16
>48 months spell	− 1.31	0.12	− 1.31	0.12	0.0003	0.16

Table 6 *Analysing the sorting effect: comparing equations 3 and 4 (Unemployment benefits)*

	Equation 3		Equation 4		Difference	
Number of observations	11465		11465			
Log-likelihood	− 36460.0		− 35670.6			
Variable	coefficient	std. error	coefficient	std. error	coefficient	std. error
Constant	− 2.08	0.014	− 1.73	0.027		
Woman			− 0.21	0.027		
Working Partner			0.094	0.028		
Child support			0.018	0.030		
Highly educated			0.20	0.061		
Disabled			− 1.26	0.089		
age 25-35 years			− 0.23	0.034		
age 35-45 years			− 0.32	0.039		
age 45-65 years			− 1.08	0.044		
6-12 months spell	− 0.62	0.036	− 0.46	0.036	0.17	0.036
12-24 months spell	− 1.41	0.052	− 1.12	0.054	0.29	0.052
24-36 months spell	− 2.05	0.11	− 1.61	0.11	0.44	0.11
36-48 months spell	− 2.64	0.22	− 2.15	0.23	0.49	0.22
>48 months spell	− 3.06	0.31	− 2.71	0.31	0.35	0.31
Hazard to other destinations						
Constant	− 2.97	0.023	− 2.64	0.041		
Woman			− 0.22	0.038		
Working Partner			− 0.13	0.039		
Child support			− 0.010	0.044		
Highly educated			0.17	0.091		
Disabled			0.48	0.056		
age 25-35 years			− 0.21	0.052		
age 35-45 years			− 0.39	0.059		
age 45-65 years			− 0.58	0.055		
6-12 months spell	− 0.22	0.048	− 0.14	0.049	0.086	0.068
12-24 months spell	− 0.50	0.056	− 0.37	0.059	0.13	0.081
24-36 months spell	− 0.46	0.083	− 0.25	0.086	0.22	0.12
36-48 months spell	− 0.36	0.12	− 0.12	0.12	0.24	0.16
>48 months spell	− 0.26	0.14	− 0.053	0.14	0.20	0.20

who have received disability benefits in the past are less able to find a job. Further, age has a strong negative effect on finding jobs, while the impact of education is positive. The impact of these variables is less pronounced for the hazard to other destinations than work.

Tables 5 and 6 still reveal a clear pattern of negative duration dependence, also after correcting for a number of individual characteristics. In the SA and UI benefits programmes, the cumulated duration effect on the hazard diminishes then by 20 to 25 %. After a spell of three to four years, the sorting process in both programmes seems to have ended; further decreases in the outflow are probably caused only by unbiased duration effects (see column with differences between the equations). Further, attention should be paid to the remarkable similarity between duration dependence in both benefits, before and after correction for observed individual characteristics. This, however, does not withstand the fact that the *absolute* level of the probability of finding a job is significantly higher for people with UI benefits. Also, it is remarkable that the results for the SA programme do not point to any sorting process in the outflow to other destinations, like non-activity or pensions; this is in sharp contrast to the same outflow from the UI programme. This is caused by the the maximum length of the period of entitlement for UI benefits. When this period has ended, unemployed workers start receiving SA benefits.

The IPR data provide us with a limited number of administrative characteristics of individuals. Probably more characteristics are relevant in explaining differences in the hazard to work. In practice, the separation of individual duration dependence and the effects of unobserved characteristics is difficult. We used two methods described earlier to test for the importance of unobserved characteristics. First, a model was estimated in which the error terms of the hazard rates are assumed to follow a Gamma distribution. The estimated parameter, describing the dispersion of this distribution, converges to a value close to zero, thus indicating that unobservable differences are not very important. We also employed the non-parametric method, in which we distinguish between different subgroups with different levels of hazard rates. This also gives no indication of unobservable heterogeneity. These results contrast with other studies with Dutch data, for example Abbring (1997) and Opstal *et al.* (1995) who find larger effects.

All in all, we believe that the use of additional information (describing part of the heterogeneity that is unobserved in the current analysis), for example on the motivation of the unemployed, may improve the accuracy of profiling techniques. However, our results stress the importance of individual duration effects, thus limiting the reach of profiling at the moment of inflow into unemployment. Unemployed job seekers - both in UI and SA - fastly become discouraged, lose their working skills and/or become stigmatized by potential employers. Therefore, targeting specific groups (at the moment of inflow into unemploment) alone bears a great risk of long term unemployment for those unemployed that are (initially) classified as having good job prospects.

6 Conclusions

To sum up, observed characteristics derived from a registered database (the IPR) can explain negative duration dependence to only a small degree. This suggests that either unobserved differences, or individual duration effects play a more important role. Our results indicate that unobserved differences are not very important. We think that more individual information may be helpful in obtaining a more accurate system of profiling, reducing deadweight risks. However, duration dependence effects at the individual level are more important. Therefore, labor market policies should not rely on profiling at the start of an unemployment spell, but also on supplemental policies, for example by encouraging search activities of all workers that have spent a certain length of time in unemployment.

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Appendix: Specification of the hazard

In the context of our model, the so called hazard rate measures the rate at which unemployed workers flow out of SA of UI benefit programmes, either into work or to other destinations. This rate, θ, is measured as the probability of leaving SA or UI over a specific (small) time interval [T, $T+dt$], given that one has received benefit up to T:

(1) $$\theta = \Pr(T < t < T+dt \mid t \geq T)$$

In our model, the time interval dt is equal to one month. The hazards or 'competing risks' have a *proportional* (or *log-linear*) structure. First, we specify the two risks as a piece-wise constant that depends only on the elapsed time in the SA or UI benefit programme:

(2) $$\theta_{\_b,i}(t_i) = \exp[\, c_{0,b} + c_{1,b}\, \mathrm{I}(6 < t_i \leq 12) + c_{2,b}\, \mathrm{I}(12 < t_i \leq 24) + c_{3,b}\, \mathrm{I}(24 < t_i \leq 36) + c_{4,b}\, \mathrm{I}(36 < t_i \leq 48) + c_{5,b}\, \mathrm{I}(t_i > 48) \,]$$

in which:

t_i is the elapsed time of receiving benefits of individual i

b indicates, respectively, the hazard to work ($b=w$) and to other destinations ($b=o$)

I is a dummy variable, which is equal to 1 if the elapsed duration lies within a certain time interval

If we look at the results in table 6, for example, then we find that the hazard to work in the second half year in the SA benefit programme is equal to exp(- 0,7408)≈ 47% of that of the first half year.

In equations 1 and 3 we estimate the model according to (2). The hazard specification can extended by adding individual characteristics (see equations 2 and 4):

(3) $$\theta_{\_b,i}(t) = \exp[\, \boldsymbol{\beta x_i} + c_{0,b} + c_{1,b}\, \mathrm{I}(6 < t \leq 12) + c_{2,b}\, \mathrm{I}(12 < t \leq 24) + c_{3,b}\, \mathrm{I}(24 < t \leq 36) + c_{4,b}\, \mathrm{I}(36 < t \leq 48) + c_{5,b}\, \mathrm{I}(t > 48) \,]$$

in which vector $\boldsymbol{x}$ = describes individual differences (like age, gender, etc..).

Also in this case the parameters describe proportional differences and can therefore easily be interpreted. For example, 45 to 65 year-olds in the SA programme have a hazard to work that is, *ceteris paribus*, only 21% (exp(-1.5511)) of that of young people under 25 years of age.

Abstract

It is well-known that the probability of an unemployed person finding a job decreases over the unemployment spell. On the one hand, this results from duration dependence at the individual level: unemployed job seekers may become discouraged, loose their working skills and become stigmatized by potential employers ('pure' individual effects). On the other hand, if there is variation between individual exit rates, there is dynamic sorting of the unemployed with low exit probabilities ('sorting effects'). Based on Dutch micro-data of social assistance (SA) and unemployment insurance beneficiaries (UI) for 1989-1996, we investigate to what extent this so-called 'negative duration dependence' is due to sorting effects, as well as 'pure' individual effects. The analysis suggests that after an unemployment spell of half a year, the decrease in the job finding rate for SA recipients can be attributed for 20% to 25% to sorting effects. After a three- to four-year period, the probability to find a job deteriorates further, but only due to individual duration effects. For UI recipients, similar results are found. From this, we conclude that profiling measures that target the inflow of unemployed with bad job prospects bear an important risk: unemployed that are initially classified as having good job prospects may also become long-term unemployed. Therefore, labor market policies should also focus on general measures, for example, by encouraging search activities of all workers that have spent a certain length of time in unemployment