SERIE RESEARCH MEMORANDA

THE DURATION OF UNEMPLOYMENT

A PROPORTIONAL HAZARD MODEL WITH NON-STATIONARY INFLOW RATES

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Researchmemorandum 1989-52 augustus 1989

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ABSTRACT

In this paper the effect of age, educational level, occupational group and regional labour market conditions on the probability of leaving the state of unemployment is estimated. We use a proportional hazard model based on aggregate data on incomplete spells of unemployment for males in the Netherlands. Effects of omitted variables and time dependence are studied in combination with a non-constant probability of becoming unemployed.
The conclusion is that the subgroups - identified with respect to age, education, occupation and region - show very different patterns of the duration of unemployment. Especially age and education have a large effect on unemployment duration, but occupational group and regional labour market conditions do also play a significant role. Model specification tests lead to the conclusion that there is unobserved heterogeneity but no time dependence in our data set. The estimation results do not change if we incorporate the effect of a non-constant probability of becoming unemployed.

1. INTRODUCTION

Most statistical methods developed in order to describe the survival time of an event stem originally from industrial engineering and the biomedical sciences. Such methods may also provide an appropriate analytical framework for studying the probability of finding a job (or leaving the state of unemployment). Hence, in the last decade, the economic analysis of duration data has also been applied to the field of labour market economics. In particular, lengths of spells of unemployment have been studied several times. Pioneering studies in the seventies were made by Salant (1977), Lancaster (1979), Nickell (1979) and Kiefer and Neumann (1979). Nowadays, models of duration have become quite popular in labour economics and have been used for analyzing various labour market issues, for example, the duration of vacancies (see for example Van Ours, 1988).

Describing unemployment duration data by means of duration models is mostly done using individual data (see for example Opstal and Theeuwes, 1986). For the Netherlands, models for the duration of unemployment on the basis of aggregate data of incomplete spells of unemployment have been specified and estimated by Kooreman and Ridder (1983). The approach of duration models using aggregate data has not yet been applied in many other studies so far.

In this paper, we will apply a duration model using a detailed data set on the population of unemployed in the Netherlands in order to identify the differences in the probability of leaving the state of unemployment for various groups on the Dutch labour market. In the specification of the duration model, we will incorporate the effects of omitted variables and duration dependence. In addition, we will take into account that the probability of becoming unemployed has varied in the past (i.e., the inflow rate is non-stationary).

Non-stationarity of the inflow rate is an element which has not been included in other studies of this type. In our opinion this is an unsatisfactory state of affairs when one wants to study the issue of duration dependence of unemployment. It is not difficult to see that duration dependence and certain patterns of non-stationary inflow rates can produce the same results for completed spells of unemployment. Therefore the possibility of non-stationary inflow rates has to be considered explicitly when one wants to study duration dependence.

Special attention will also be paid to regional differences in the probability to leave the state of unemployment. By doing so, demand side aspects of the labour market can be incorporated in the analysis.

The paper is organized as follows. Models of duration will be the subject of section 2. In subsection 2.1 we will discuss the hazard function, whilst in subsection 2.2 we will derive the distribution function of the duration model using incomplete spells of unemployment. Next, we will derive the likelihoodfunctions of the hazard models using aggregate data (with and without a non-stationary inflow rate) in subsection 2.3. In section 3, we will present the empirical results of the estimation of the duration models. After having discussed the data set in subsection 3.1, we will turn to the results. First, we will present and discuss the results of the exponential model in subsection 3.2. Next, the issue of modelspecification will be raised (in subsection 3.3) and we will study the impact of a non-stationary inflow rate in subsection 3.4. Concluding remarks are given in section 4.

2. DURATION MODELS

2.1. The hazard function

The central concept in the statistical analysis of the duration of unemployment is the conditional probability of leaving the state of unemployment, given the current length of unemployment. The conditional probability of the termination of being in the state of unemployment is called the hazard and the length of an incomplete spell of unemployment the survival time (these terms do originally come from the medical sciences).

A question often addressed in the analysis of duration data of unemployment is whether the conditional probability of leaving the state of unemployment depends on the length of the spell of unemployment. The hazard function approach enables us to choose a constant hazard as a natural special case (or a null hypothesis) and deviations from this special case (for example, a decreasing probability to leave the state of unemployment caused by a decreasing intensity of search efforts of the unemployed or by a fall in the level of the unemployment benefits) can then be tested. The exponential distribution (sometimes termed the memoryless distribution) has the property of a constant hazard rate and will therefore be used as the null hypothesis in hazard models tested in this paper.

We will first examine the general distribution of the duration of unemployment. We define the distribution function

$$G(\underline{t}) = Pr(\underline{t}<t) \qquad (1)$$

which specifies the probability that the random variable $\underline{t}$ is less than some value t. The corresponding density function is $g(\underline{t})=dG(\underline{t})/dt$.

Now we define the hazard function

$$\delta(t) = \frac{g(t)}{1 - G(t)} \qquad (2)$$

which gives the rate at which spells will be completed at duration time t, given that they last until t.

Studies in the context of job search behaviour on the labour market often also make use of the hazard function approach (see for example Lancaster, 1979 and Nickell, 1979). The hazard function is then seen as the product of the probability of receiving a job offer multiplied by the probability that the (in this case) unemployed individual will accept this offer. The decision to accept the offer depends on the wage of the job offer compared to the minimum wage the unemployed is willing to work for (the so-called reservation wage). Reservation wages are usually not known, however for an exception with data on the Dutch labour market, see Ridder and Gorter, 1986 and Van den Berg, 1988.

One can write for the probability of leaving the state of unemployment:

$$\delta(t)dt \tag{3}$$

where we have to choose an appropriate functional form for $\delta(t)$.

The most general form of the hazard function is a specification in the form of the proportional hazard model (PHM). In the PHM we have

$$\delta(t)dt = \theta(x).\tau(t).v.dt \tag{4}$$

The first term of the product, i.e. $\theta(x)$, shows the effect of the explanatory variables (x) on the hazard rate. The second term of the product $\tau(t)$, takes account of the time dependence of the probability of leaving unemployment, whilst the third term (v) is a random error term representing the effect of omitted variables.

With an error term equal to 1 and no time dependence of the hazard rate (i.e., $\tau(t)=t$), we arrive at the natural case of the hazard model, namely the exponential distribution with a constant hazard (equal to $\theta(x)$). Without an error term however, unrecognized heterogeneity may bias the parameters of the duration model. This is due to the so-called "weeding-out" process. In a subgroup of individuals with a higher average leaving rate, the people with better unobserved characteristics will leave the state of unemployment first, causing the average hazard of the survivors to fall and become more similar to the average hazard of the subgroup with a lower average leaving rate. The effect of the observed characteristics will thus be biased if an error term is excluded (for an analytical approach, see Lancaster, 1979).

Another cause of a decreasing hazard in time is the time dependence of unemployment duration. This may be explained in terms of job search theory as follows: if the positive effect of duration on the probability of job acceptance is less than its negative effect on the probability of a job offer, then there is negative duration dependence. Although both the inclusion of unobserved heterogeneity and of negative duration dependence leads to a decreasing hazard rate in time, it has been shown (by Elbers and Ridder, 1982) that it is possible to distinguish between sample heterogeneity and duration dependence in a proportional hazard model if there are regressors included.

In section 2.4 we will present the functional form of the function $\tau(t)$ and the distribution of the error term.

2.2. The distribution function of an incomplete spell of unemployment in the case of non-stationary inflow rates

The distribution function of the length of a completed spell of unemployment is entirely determined by the following hazard function (see Lancaster, 1979)

$$G(t) = 1 - \exp \int_0^t \delta(s)ds \tag{5}$$

Now, we want to derive the density function of incomplete spells of unemployment, because the data set of the unemployed we will be using, consists only of incomplete spells. Following Kooreman and Ridder (1983), we find that the density function of incomplete spells of unemployment h(t) can be written in terms of G(t) and the corresponding density function g(t). Kooreman and Ridder have made in this framework two crucial assumptions:

1) Conditioning of the time at which unemployment started is suppressed.
2) The probability of becoming unemployed is constant over time.

Then it follows that:

$$h(t) = \frac{\Pr(\underline{t} \geq t)}{\int_0^\infty \Pr(\underline{t} \geq s)ds} = \frac{1 - G(t)}{E(\underline{t})} \qquad (6)$$

In this paper, however, we will modify the second assumption and alternatively assume that the inflow rate has varied in the past. Consider an individual who is unemployed at t=0, and suppose that the probability of becoming unemployed has changed at time-t_0 from q_0 to q_1, at time $-t_1$ from q_1 to q_2, etc. This varying pattern can be shown as follows:

q_{n+1}	q_n		...	q_3	q_2	q_1	q_0		probability of inflow
	$-t_n$	$-t_{n-1}$	...	$-t_3$	$-t_2$	$-t_1$	$-t_0$	0	time

Then the density function of the elapsed duration becomes

$$h^*(t) = \begin{cases} \dfrac{q_0 \Pr(\underline{t} \geq t)}{N} & \text{for } -t_0 \leq t < 0 \\[2ex] \dfrac{q_1 \Pr(\underline{t} \geq t)}{N} & \text{for } -t_1 \leq t < -t_0 \\ \quad\vdots & \\ \dfrac{q_{n+1} \Pr(\underline{t} \geq t)}{N} & \text{for } t < -t_n \end{cases} \qquad (7)$$

with

$$N = q_0 \int_0^{t_0} \Pr(\underline{t} \geq s)ds + q_1 \int_{t_0}^{t_1} \Pr(\underline{t} \geq s)ds + \ldots + q_{n+1} \int_{t_n}^{\infty} \Pr(\underline{t} \geq s)ds$$

The validity of this alternative specification will be tested in subsection 3.4.

2.3. The likelihood functions of proportional hazard models with aggregate data

As will be further discussed in subsection 3.1, we do not have data on the individual duration of unemployment, but the individual durations are grouped in duration classes. If we consider a homogeneous group of unemployed then we can find the proportion of unemployed of that group having an incomplete spell of unemployment in a duration class by using the same density function for all individuals in that group and next integrate over the relevant duration class.
Thus for the first duration class (0-1 month) and a homogeneous group i we find

$$p_{1i} = \int_0^1 h_i(t)dt \tag{8}$$

In our model we have data on the whole population of unemployed subdivided in groups according to a number of characteristics. For each subgroup we know the number of unemployed in each of the duration classes. So we can write the log-likelihood function of the data as follows:

$$\log L(\mu) = \Sigma_i \; \Sigma_d \; n_{id} . \log \; (p_{id} \; (\mu)) \tag{9}$$

where μ denotes the parameters of the model; index i refers to the subgroup and index d refers to the duration class.

Now it is evident from the previous discussion that we have two main classes of models, namely

a) proportional hazard models with stationary inflow rates
b) proportional hazard models without stationary inflow rates

For each of the classes, we consider four special cases of the specification of $\delta(t)$ (see also Kooreman and Ridder, 1983). We will present those four cases and show whether the model can take account of a non-constant probability of leaving the state of unemployment and whether an error term is included.

model	sample heterogeneity	duration dependence
I	no	no
II	no	yes
III	yes	no
IV	yes	yes

The function representing the explanatory variables is defined as the following exponential function

$$\theta(x) = \exp\ (x'\beta) \tag{10}$$

with β the vector of coefficients to be estimated. In the model with duration dependence (II and IV), we will use a Weibull specification:

$$\tau(t) = \alpha\ t^{\alpha-1},\ \alpha>0 \tag{11}$$

If $\alpha=1$ there is no duration dependence; if $\alpha<1$ there is negative and if $\alpha>1$ there is positive duration dependence. In the models with an error term (included to take account of the unobserved heterogeneity) we assume v has a gamma distribution with mean 1 and variance σ^2:

$$f(v) = ((\sigma^2)^{-\sigma^{-2}} / \Gamma(\sigma^{-2})).\ v^{\sigma^{-2}-1} .\exp(-v\sigma^{-2}) \tag{12}$$

The proportional hazard specification ($\delta(t)=\theta(x).\tau(t).v$) implies the following distribution function for a single spell of unemployment $\underline{t}$,

$$1\text{-}G(t) = E_v\ \{ \exp \left[- \exp^{x'\beta} .\underline{v}. \int_0^t \tau(s)ds \right] \} \tag{13}$$

where E_v indicates that the expectation is taken with respect to the distribution of v (see Kooreman and Ridder, 1983).

The four cases then lead to the following specification of 1-G(t)

I $$1\text{-}G(t) = \exp(-\theta(x)t) \tag{14}$$

II $$1\text{-}G(t) = \exp(-\theta(x)t^{\alpha}) \tag{15}$$

III $$1\text{-}G(t) = (1+\sigma^2\theta(x)t)^{-\sigma^{-2}} \tag{16}$$

IV $$1\text{-}G(t) = (1+\sigma^2\theta(x)t^{\alpha})^{-\sigma^{-2}} \tag{17}$$

For each of these specifications, h(t) and $h^*(t)$ can be found (by using (6) and (7)) and used to evaluate the likelihood function. Therefore we have to integrate the density functions h(t) and $h^*(t)$ (see equation (8)). For the cases I and III this can be done analytically. In the other two cases, we have to use numerical integration techniques (e.g., from the NAG-library). The resulting likelihood is maximized using a quasi-Newton algorithm which requires no (analytical) derivatives (see the software from the NAG-library). The (asymptotic) variance matrix of the maximum likelihood estimators is estimated by the inverse of the (numerically calculated, except for the exponential model) Hessian of the min-loglikelihood function

$$\mathrm{var}(\mu^*) = \left[\frac{\delta^2 \ln L(\mu)}{\delta\mu\delta\mu'} \right]^{-1}_{\mu=\mu^*} \tag{18}$$

with μ^* the maximum likelihood estimate of μ.

3. EMPIRICAL RESULTS

3.1 The data

The starting point of our data analysis is the entire population of unemployed in the Netherlands officially registered at the regional Labour Exchange Offices. The use of this data set has both advantages and disadvantages. To start with the former, the data set is complete (all registered unemployed are included). The data set is also cross-classified according to a number of characteristics. The duration of registration and the duration of "availability" (for a job) are the essential characteristics for the duration model. For obvious reasons, we will use the second duration characteristic in our model. In addition, the data is subdivided into subgroups according to sex, age, educational level, occupational group and region, which make the data set highly informative. This form of the data determines also the choice of the regressors in the hazard model. We will include a continuous variable for age, while we will use dummy variables for the categorical variables occupational group, level of education and region of residence. For each subgroup of unemployed, we know the distribution over 11 "duration of availability" classes, starting with the duration class "less than one month" and ending with the duration class "more than four years unemployed and available for work"[1].

Another advantage of the data is the flexibility in the choice of the level of spatial aggregation, which enables us to define separate regional labour markets. This will be done on the basis of the interregional mobility of job searchers who have found work in another region (see, SEO 1988, p22-26). In this report, the following labour market areas are distinguished.

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[1] More specific information about our data set is presented in appendix A.

region		provinces
1	North-East	Groningen, Friesland, Drenthe, Gelderland and Overijssel
2	North-West	Noord-Holland, Utrecht and Flevoland
3	South-West	Zuid-Holland and Zeeland
4	South-East	Noord-Brabant and Limburg

with interregional mobility figures as shown in Table 3.1.

living (in 1980) in region	working (in 1981) in region 1	2	3	4	abroad/unknown
1	81	5	3	1	10
2	3	84	4	-	9
3	1	4	83	1	9
4	2	2	4	79	12

Table 3.1. Interregional mobility in percentages.

Note that the unemployed with a high level of education will probably have a larger labour market area than the regions we have chosen above. For practical reasons, we do not incorporate the effect of a different search area for those groups on the leaving rate and this effect will therefore be included in the effect of a high education.

There are also disadvantages of the data of the unemployed registered at the various Labour Exchange Offices. It frequently occurs that people who have left the stock of unemployed remain incorrectly registered as unemployed for some time. This effect leads to a serious overestimation of the number of unemployed people. Some studies have estimated the effect of "dirty data" to be about 40% of the stock, which is very high (see for example, Dekker et al.,1986). However, for the study of the effects on the duration of unemployment it is the distribution of the various groups of the stock over the duration classes which matters. From a study of the differences in distribution of the "biased" stock and the "unbiased" stock over the categories of a number of relevant characteristics could be concluded that these distributions were approximately the same (see Dekker and Detmar, 1987). In particular, the characteristics age, level of education, occupational group and region and duration of registration were examined which are also the components of our data set. The difference in the distribution of the stock with respect to duration is the highest for the duration class "more than 3 years unemployed" (namely 4%), but for the other classes the differences are less than 2% (see Table 3.2).

duration class		"dirty data"		"clean data"	
		number	%	number	%
< 3	months	109.300	16	64.800	15
3-5	months	99.700	14	52.200	12
6-11	months	116.900	17	63.000	15
12-23	months	121.500	18	75.000	18
24-35	months	72.900	11	43.700	10
≥ 36	months	171.800	25	120.300	29
total		692.200	100	419.000	100

source: Dekker and Detmar (1987)

Table 3.2. Distribution of the unemployed males (March 1987).

Another disadvantage is the remaining heterogeneity within a subgroup, but this is inherent to the choice of the use of aggregate data. Relevant missing variables may be:

1) Income.
Usually after a period of six months the unemployment benefit (for those who were previously unemployed) drops to the minimum subsistence level. The necessity of a labour income may then arise when (household) expenditures are based on previous labour income. As a result, search intensity may increase and/or the reservation wage may fall.
2) Nationality.
Immigrants from Mediteranean countries and from Surinam may have more difficulties to get (and maintain) jobs as a result of social, cultural and linguistic differences. Discrimination by employers may also play a role here.
3) Family status / social environment.
The household composition may lead to the necessity of the provision of family income or - on the other hand - to a free choice between labour and leasure because of the (labour) income of the other members of the household. The social environment and the number of contacts do also influence the attitude to work and the knowledge of job opportunities of the unemployed individual.
4) Labour Market History.
Not only the current spell of unemployment is important for the outcome of the duration of unemployment. The length and the number of previous spells in employment and unemployment may as well have an impact on the probability to leave the state of unemployment.

In order to make a correction for the effect of the unobserved heterogeneity, we will include an error term in the duration model.

Because we will include a non-stationary probability of becoming unemployed in the duration model, we need data on the inflow rates of the unemployed. For this purpose, we use the inflow data presented by the Ministry of Social Affairs and Employment on people becoming (registered as) unemployed at the Labour Exchange Office (see "De Arbeidsmarkt", 1986-1988). We have to emphasize that these figures are not entirely reliable, because of the difference in the moment of registration and availability for a job (especially regarding young people who are going to leave school and register in advance). We will use the inflow rates as <u>relative</u> figures; so if the bias in the inflow rate does not vary throughout the year then this will not have much consequences for the estimations of the model. However, in Spring of each year there will be a bias compared to other seasons due to the inflow of (young) people who are going to leave school and register in advance.

We will distinguish six different periods (corresponding to the length of the duration classes of the data), namely
a) less than one month ago
b) between one month and three months ago
c) between three months and six months ago
d) between six months and nine months ago
e) between nine month and twelve months ago
f) more than one year ago,
and calculate the average inflow rate for all these periods.

In this paper, we will use data on the stock of unemployed males measured on the first of November 1988. In theory, we should calculate different inflow rates for each subgroup distinguished in the model, but for practical and computational reasons we will use the average inflow rate for unemployed men in the relevant period. Then we get

period	inflow rate per month (10^{-3})
Okt 1988	11.4
July 1988 - Sept 1988	13.7
May 1988 - June 1988	11.6
Febr 1988 - Apr 1988	11.5
Nov 1987 - Jan 1988	14.7
before Okt 1987	12.6

<u>Table 3.3.</u> Non-stationary inflow rates for men before November 1988

3.2. <u>Estimation results of the exponential model</u>

From the results of the basic exponential model (model type Ia) presented in Table 3.4., we observe that both the continuous variable AGE and the dummy variables occupational group, level of education and region of residence play an important role in the determination of the probability of leaving unemployment (the hazard rate). This basic model is characterized by a constant hazard rate and stationary inflow rates.

variable		coefficient	(t-values)
constant		3.187	(168.9)
ln(AGE)		-1.628**	(-334.0)
occupation	- general	-0.257	(-46.4)
	- industrial	-0.074	(-13.9)
	- general services	-0.268	(-45.9)
education	- primary	-0.728	(-122.7)
	- low	-0.459	(-79.7)
	- middle	-0.188	(-31.1)
region	- North-East	-0.135	(-29.7)
	- North-West	0.049	(10.4)
	- South-West	0.041	(8.6)

* LL = - 1095223

** The absolute value is the elasticity of the mean unemployment duration with respect to AGE.

*** The reference categories for occupation, education and region are the administrative service sector, high education and the South-East region respectively.

Table 3.4. Maximum likelihood estimates of the exponential model.

We observe that all coefficients are highly significantly different from 0. Remember that we have divided the unemployed in 320 subgroups, so the number of observations (Σ_i 320 * 11 duration classes * number of individuals in subgroup i) is statistically infinite. Especially the coefficient of age and the level of education show a highly significant effect on the hazard rate.

The elasticity of the mean unemployment duration with respect to age is about 1.6, which is high compared to the study of aggregate data by Kooreman and Ridder (1983). In their article, they presented an estimated value of 1.2 for the age-elasticity of the mean unemployment duration for men in the year 1979. Almost a decade later, the age-elasticity has grown with 33%. Apparently there has been an enormous growth of the flow into unemployment of the elderly employees in the beginning of the 1980's. A large number of these people seem to have failed to escape the state of unemployment ever since.

Considering the effect of the occupational group of the unemployed on the hazard rate, we observe a substantial negative effect for the group with no specific occupation and the people who were working in the general service sector (compared with the unemployed registered in the group of the administrative service sector for which the coefficient is set to 0 in order to identify the effect on the leaving rate of the other categories of the dummy variable). For industrial workers (who are mainly concentrated in the construction and the metal sector), we find a much lower but still negative effect.

The influence of the level of education is - as is well-known - remarkably high. Belonging to the group of unemployed who have only finished their primary school does more than double the mean duration of unemployment (see Table 3.5), compared to the unemployed with the highest level of education (academic level). For the lowly educated unemployed the duration prospects are slightly better, but mean duration is still 1.6 times as high as for the highly educated unemployed. Even for those with an education of a medium level, the average duration is 20% higher now. The multiplicative effect on the mean duration of unemployment of various distinct features appears to lead to the following results:

a) <u>occupational group</u> (relative to administrative services):	
- general	1.29
- industrial	1.08
- general services	1.31
b) <u>level of education</u> (relative to the highest (academic) level):	
- primary	2.07
- low	1.58
- middle	1.21
c) <u>region</u> (relative to the South-East region):	
- North-East	1.15
- North-West	0.95
- South-West	0.96

<u>Table 3.5.</u> The effects on the mean duration of unemployment.

Next, we take a look at the effect of the region of residence of the unemployed on the leaving rate. As we have seen in section 3.1, it is reasonable to assume (for most sub-groups) that the unemployed will search for jobs only within the region. It is of course also worth noting that differences in the regional economic structure and the resulting regional demand for labour may lead to quite different opportunities for the unemployed.

We observe a 15% higher average duration of unemployment (ceteris paribus) for the unemployed in the North-East region (which includes Groningen, Friesland, Drenthe, Overijssel and Gelderland) compared to the reference region South-East (Noord-Brabant and Limburg). In the North-West and South-West region, the core of the Netherlands, there is a lower mean duration of unemployment of respectivelly 5 and 4%[2]. This result is consistent with data on the number of vacancies relative to the number of unemployed in those regions (see Table 3.6).

In determining the number of vacancies, we have used the most recent vacancy survey among firms of the Central Bureau of Statistics (January 1988), because the number of registered vacancies at the Labour Exchange Office is an underestimation of the "real" number (firms are not obliged to register their vacancies).

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[2] Folmer and Van Dijk (1988) did not find a regional effect on the duration of unemployment, but they used a different approach in which they compared the composition of groups with different spells of unemployment.

region	V/U*
North-East	6.4
North-West	11.9
South-West	10.3
South-East	9.2

* the vacancy-unemployment rate (V/U) is divided by 100.

Table 3.6. Regional variation in the vacancy-unemployment ratio.

In order to examine the effect of regional demand on the probability of leaving the state of unemployment we will next estimate the basic model with the vacancy-unemployment ratio in stead of the regional dummy variable[3]. This makes it possible to determine to which extent the regional effect on the duration of unemployment is related to regional demand. In addition, we will investigate the robustness of the other parameters of the model against a different specification of the regional effect.

The estimation results show that the other parameters (and the value of the loglikelihood) do not change notably. The elasticity of mean duration of unemployment with respect to the vacancy-unemployment ratio is estimated to be 0.32. For the multiplicative effect on the mean duration we then get

region	dummy-variable	V/U ratio
North-East	1.15	1.11
North-West	0.95	0.92
South-West	0.96	0.97
South-East	1.00	1.00

We may conclude that the differences in the regional effects are largely due to differences in regional demand.

The positive effect of the North-West and the South-West region seems to contradict the fact that the mean duration of unemployment in the large cities situated in those regions is higher than average. One must be aware, however that in the large cities the compostion of the unemployed with respect to their personal characteristics (observed in this model), namely age, educational level and occupation. In other words, the high level of the duration of unemployment in certain parts of the NW and ZW regions are probably more due to the unfavourable personal characteristics of the unemployed and/or unfavourable local labour market conditions than the labour market condition of the region as a whole. In the urban labour market there may be large discrepancies between labour demand (highly qualified people for the high tech/service sector) and supply (low educated people in the traditional sectors) (see Kruyt, 1987).

Finally, we will compare the mean duration of unemployment of people in a number of different subgroups in order to give an impression of the absolute value of the mean duration of

[3] It can be demonstrated that the number of unemployed can be included as an independent variable (see Van Ours and Ridder, 1988). Intuitively, one can argue that in the case of a large number of unemployed the influence of the V/U ratio on the probability for an individual to leave the state of unemployment is negligibly small.

unemployment and to show the extreme values of the average duration as a consequence of the combination of labour market characteristics in a subgroup. For reaching the maximum value of the mean duration on unemployment, we have to look at the values for the different subgroups in the region North-East with a general occupation and for the minimum we have to display the values for the different subgroups in the region North-West with an occupation belonging to the administrative sector (see Table 3.7).

We see that the absolute minimum for the average duration of unemployment is 7 months (for young and high educated people) indicating that despite "good" labour market characteristics the average search time of the unemployed is still longer than ½ year. This figure must not be confused with the average search time of finding a job for all job searchers (e.g. people who leave school), which is of course much less because we do not observe the people who get a job immediately (without being unemployed).

(I) region : North-East
occupation : general

		education			
		primary	low	middle	high
age	young	24	18	14	12
	middle	51	39	30	25
	old	86*	66	50	42

(II) region : North-West
occupation : administrative services

		education			
		primary	low	middle	high
age	young	15	12	9	7**
	middle	33	25	19	16
	old	55	42	32	27

* maximum value
** minimum value

Table 3.7. Expected mean duration of unemployment in months

The maximum value for the average duration of unemployment is about 7 years (for old people with only primary school) indicating that most of these people (55 years old or more) will never find a job again.

3.3. Model specification

In section 3.2., we have presented the estimation results on the basis of an exponential distribution for the duration of unemployment (see 14). We have also interpreted the values of the coefficients with respect to the effect on the average duration of unemployment.

In the analysis of the previous section we have made the assumption that the hazard rate is constant over time. However, the leaving rate may possibly drop in due course. One cause of a decreasing hazard rate in time is the "weeding out" process, which leads to a gradual change in the composition of the stock of unemployed in favour of the people with less favourable unobserved labour market characteristics. Another cause of a hazard rate declining over time is the effect of a decrease in the number of jobs offered to unemployed individuals with a higher duration of unemployment. A countervailing force here could be a reduction in the reservation wage of the unemployed individual, but without a single job offer this obviously has no effect on the leaving rate.

As we have already mentioned in section 2.1., it is possible to specify a non-constant hazard function. By taking the exponential case as the null hypothesis, we can test whether or not there is a falling hazard rate. In addition, we are able to separate the effect of unobserved heterogeneity within the subgroup and of the time-dependence of the hazard rate by means of model specification IV (see section 2.3.), so we can find to what extent the fall in the hazard rate is due to unobserved heterogeneity or time dependence.

Note that the inclusion of an error term is indispensible when we want to determine whether there is a "true" time dependence effect, because omitting the error term may lead to spurious time-dependence (see also Kiefer, 1988).

We have to emphasize that conclusions about the effects of the regressors made on the basis of proportional hazard models incorporating the possibility of unobserved heterogeneity and time-dependence are dependent on arbitrary assumptions about the specification of the distribution of the error term and the functional form of the time-dependence ($\tau(t)$). The estimation results will thus also show the robustness of the coefficients against the different specifications of the hazard function.

In table 3.8. we present the results of the maximum likelihood estimates for the hazard models with a stationary inflow rate. The estimations results are obtained by combining (6),(8) and (9) and using the general maximum likelihood program GRMAX. As mentioned in section 2.3., dependent on the specification of the hazard either analytical or numerical integration techniques are needed. For the latter we used the computer routines from the NAG-library.

Case		I	II	III	IV
constant		3.187	2.818	3.668	3.670
ln(AGE)		-1.628	-1.063	-1.556	-1.558
occupation	- general	-0.257	-0.174	-0.286	-0.286
	- industrial	-0.074	-0.047	-0.058	-0.059
	- general services	-0.268	-0.174	-0.267	-0.268
education	- primary	-0.728	-0.471	-0.771	-0.772
	- low	-0.459	-0.286	-0.420	-0.421
	- middle	-0.188	-0.120	-0.147	-0.149
region	- North-East	-0.135	-0.098	-0.143	-0.143
	- North-West	0.049	0.026	0.045	0.047
	- South-West	0.041	0.015	0.029	0.030
time-dependence (α)		1.000*	0.607	1.000*	0.999
error variance (σ^2)		0.000*	0.000*	0.317	0.315
min-loglikelihood (*1000)		1095.223	1081.762	1080.851	1080.843

* coefficients are fixed

Table 3.8. Maximum likelihood estimates.

The improvement in the value of the loglikelihood for model type III compared to the basic exponential model (I) is highly significant on the basis of a X^2-test (with test-statistic $T = -2*(\log(L_{III})-\log(L_I))$. Model type II does also give a major improvement of the loglikelihood. However, the estimates of the explanatory variables and the time-dependence effect are not reliable because the error term is excluded while there is unobserved heterogeneity in the subgroups (see outcomes model type III)[4]. Model type IV does not give a significant decrease of the loglikelihood and the estimated coefficients (including α) are almost the same as in model type III. So the outcomes of the loglikelihoods and the values of α and σ^2 indicate that there is unobserved heterogeneity, but no "true" duration dependence.

The observation of no "true" duration dependence implies (within the context of our model) that selectivity of employers in the process of hiring new employees is more based on (time-constant) characteristics like occupational group, level of education and also age (time-constant relative to the duration of unemployment) than on the elapsed duration of unemployment of the individual. In other words, according to the estimates of the models some people remain longer unemployed because they do not have the "right" characteristics and there is no additional effect (controlling for the effect of the characteristics) of the elapsed duration of unemployment.

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[4] The effects of the regressors on the mean duration of unemployment can be compared with the exponential model by dividing the outcomes by α=0.607.

The analysis of the presence of duration dependence (controlling for observed and unobserved effects) is a difficult issue. Arbitrary assumptions about the functional forms are needed, within the context of a proportional hazard model, to identify the heterogeneity and duration dependence effect. For the Netherlands, we will summarize the outcomes of the duration dependence effect of unemployment estimated by (multi)-proportional hazard models.

study		data	duration dep.
Kooreman and Ridder	(1983)	male (79)	no
Den Broeder	(1986)	young (82-84)	no
Opstal and Theeuwes	(1986)	young (84)	?
Ridder	(1987)	male (73-83)	no
Theeuwes et al.	(1987)	male (80-85)	no
Ter Huurne	(1988)	young (84-86)	yes
Gorter et al.	(1989)	male (88)	no

On the whole, we notice that for males there is not much evidence of an autonomous duration dependence effect. For young people (among which the first entrants) there might be a negative impact of the spell of unemployment on the leaving rate.

A second important observation of Table 3.8. is the impact of the error term on the effects of the regressors. In theory, these effects are biased downward if unobserved effects (uncorrelated with the observed regressors) are omitted. We observe a smaller effect of age in the model with an error term (III), while we would expect to find a larger effect. A possible explanation may be that the unobserved effects are <u>correlated</u> with age (for example, motivation or search intensity). As a consequence, the bias in the effect of age points in the opposite direction. For the dummy variables occupational group, level of education and region we do find a larger negative effect of the least favourable group compared to the reference group.

In addition, the estimates and standard errors of the model type III are presented in Table 3.9[5]. In appendix B, we will present the estimation results of model type III with the vacancy-unemployment ratio instead of the regional dummy variable.

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[5] For the models type II and IV we did not - in first instance - compute standard errors because of the excessively high computational burden of the numerical calculations of the asymptotic variance matrix (we have 3520 categories!). Fortunately, model type II had to be rejected because of the biased estimates (due to the omission of an error term) and model type IV cannot improve the model specification of type III. So model type III turned out to be the "best" model and we decided to compute the standard errors for this model only.

variable		coefficient	(t-values)
constant		3.668	(159.3)
ln(AGE)		-1.556	(-265.8)
	- general	-0.286	(-40.9)
occupation	- industrial	-0.058	(-8.5)
	- general services	-0.267	(-36.1)
	- primary	-0.771	(-100.9)
education	- low	-0.420	(-56.9)
	- middle	-0.147	(-18.6)
	- North-East	-0.143	(-25.3)
region	- North-West	0.045	(7.7)
	- South-West	0.029	(5.7)
error variance (σ^2)		0.317	(199.0)

Table 3.9. Maximum likelihood estimates and standard errors of model type III.

In conclusion, the exponential case (with a constant hazard rate) is rejected in favour of the model with an error term included. Next, adding the possibility of time-dependence to this model does not change notably the estimation results. The elasticity of the mean duration of unemployment with respect to age is (surprisingly) slightly less and the small changes in the coefficients of the dummy variables are in correspondence with the theory of unobserved (uncorrelated) effects.

3.4. The impact of a non-stationary inflow rate

In the previous section, we have tested whether the exponential specification must be rejected in favour of a specification of the hazard with a non-constant rate. We have found that adding an error term does significantly improve the modelspecification, but the simultaneous specification of an error term and time-dependence does not lead to a different outcome of the loglikelihood and the parameter of the time-dependence effect (α=0.999).

In addition to the test of a non-constant probability of leaving unemployment, we want to consider the impact of a non-constant probability of becoming unemployment on the hazard rate.

Including the effect of a non-stationary inflow rate may lead to different values of the parameters. In an attempt to make this point intuitively clear one may consider the following example. Suppose the probability of becoming unemployed was smaller in the period "less than one year ago" compared to the period "more than one year ago". Then the relative share of the long-term unemployed is higher, which will lead to a reduction of the hazard rate over time. One way to model a reduction of the hazard rate is to enlarge the negative time-dependence effect. The other way is an increase of the variance of the error term. The parameters of time-dependence and unobserved heterogeneity of the model may thus be biased if we do not take account of a non-stationary inflow rate. The different composition of the stock of unemployed (due to the higher inflow rate in the past) could also lead to a change in the parameters of the observed characteristics if the additional long-term unemployed share the same characteristics (for example, relatively more people with only primary school did become unemployed in the past). In short, the estimation results may be subject to a selection bias.

In this section, we want to examine the influence of a non-stationary inflow rate on
1. the parameters of the explanatory variables
2. the parameters of time-dependence and unobserved heterogeneity.

This will be done by estimating model specification III and IV incorporating a non-stationary inflow rate[6]. In section 2.3., we have derived the density function of the elapsed duration of unemployment in case of a non-stationary inflow rate (see (7)). The likelihood functions are then obtained by using (7),(8) and (9) for each model. In Table 3.10. we will show the maximum likelihood estimates on the basis of inflow data as presented in Table 3.3 (section 3.1).

Case		IIIa*	IIIb**	IVa*	IVb**
constant		3.668	3.675	3.670	3.679
ln(AGE)		-1.556	-1.557	-1.558	-1.558
occupation	- general	-0.286	-0.287	-0.286	-0.291
	- industrial	-0.058	-0.056	-0.059	-0.056
	- general services	-0.267	-0.267	-0.268	-0.271
education	- primary	-0.771	-0.770	-0.772	-0.770
	- low	-0.420	-0.421	-0.421	-0.425
	- middle	-0.147	-0.144	-0.149	-0.144
region	- North-East	-0.143	-0.144	-0.143	-0.148
	- North-West	0.045	0.051	0.047	0.050
	- South-West	0.029	0.036	0.030	0.040
time-dependence (α)		1.000	1.000	0.999	0.996
error variance (σ^2)		0.317	0.315	0.315	0.317
Loglikelihood (*1000)		1080.851	1081.746	1080.843	1081.668

* stationary inflow rates
** non-stationary inflow rates

Table 3.10. Maximum likelihood estimates of models with and without stationary inflow rates.

[6] We have chosen model type III and IV on the basis of the model specification tests of the previous section.

We observe that the conclusion (drawn on the basis of models with stationary inflow rates) of the existence of unobserved heterogeneity and no presence of "true" duration dependence, remains the same on the basis of models with non-stationary inflow rates. In addition, the effects of age, occupational group and level of education are hardly influenced by the incorporation of a non-stationary inflow rate. Finally, the effect of the region, which can be seen as an indicator of regional demand, does change slightly.

In summary, the estimation results are approximately the same for the models with or without a non-stationary inflow rate. This might be due to the small variation of the inflow rate and/or the combined effect of above and below average values of the inflow rates (see Table 3.3). If we would differentiate the inflow rate according to region (and possible other characteristics), the estimation results may be changed more considerably. In principle, it is an improvement of the model specification to take account of a varying probability of becoming unemployed, but in this empirical application <u>no real changes</u> have been found.

4. CONCLUDING REMARKS

We have specified and estimated proportional hazard models using aggregate data. Starting from the basic exponential model, we have extended the hazard model with an error term, the possibility of time-dependence and the combination of both. In the end, we have adjusted the model for a non-stationary inflow.

From the empirical application with Dutch data (unemployed males in November 1988) we have learned that:

(1) The identified subgroups on the labour market show very different patterns of the duration of unemployment.
Especially age and educational level are important determinants of the duration of unemployment, but the occupation and region do also play a significant role. The combination of the most unfavourable characteristics (old, primary school, general occupation, North-East region) lead to an expected duration of more than 7 years. On the other hand, the people with the best identified characteristics (young, high education, administrative service sector, North-west region) do still have an expected duration of 7 months.

(2) The inclusion of an error term is indispensible.
The overall fit of the model with an error term is improved remarkably compared to the basic exponential model. Together with the significance of the error variance this implies that there is unobserved heterogeneity in the sample. In this case, exclusion of the error term in a model with a decreasing hazard due to duration dependence leads to biased estimates of both the effects of the regressors and the autonomous effect of elapsed duration on the leaving rate.

(3) There is no duration dependence present if we control for unobserved heterogeneity within the subgroup.
After controlling for the observable effects of age, education, occupational level and for the unobservable effects by means of an error term, no additional autonomous effect of the elapsed duration of unemployment on the probability of leaving the state of unemployment can be found.

(4) The modification of the hazard model in the case of non-stationary inflow is necessary from a theoretical point of view. However, in this application we did not find much difference between the models with and without non-stationary inflow rates.

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Appendix A

In this appendix, the number of unemployed males cross-classified with respect to the duration class and the region is shown to get an impression of our data set. In the model, we have used a much more detailed data set: the number of unemployed males cross-classified with respect to duration, region, age, educational level and occupational group. In this way, more than 3500 different categories were distinquished on the Dutch labour market.

unemployed (absolute figures)

duration class	N-E	N-W	S-W	S-E
0 - 1	9542	8221	7227	6869
1 - 3	18689	18248	15916	14160
3 - 6	25579	20225	18515	17067
6 - 9	10753	9771	9624	7431
9 -12	9995	8838	8267	7090
12-18	13992	12202	11581	9588
18-24	8392	8390	8095	6188
24-30	7183	6730	6249	5282
30-36	5351	4705	4886	3574
36-48	8856	8281	7252	5430
48- ∞	32231	18611	21949	20729
total	150563	124222	119561	103408

unemployed (relative share)

duration class	N-E	N-W	S-W	S-E
0 - 1	6.3%	6.6%	6.0%	6.6%
1 - 3	12.4%	14.7%	13.3%	13.7%
3 - 6	17.0%	16.3%	15.5%	16.5%
6 - 9	7.1%	7.9%	8.0%	7.2%
9 -12	6.6%	7.1%	6.9%	6.9%
12-18	9.3%	9.8%	9.7%	9.3%
18-24	5.6%	6.8%	6.8%	6.0%
24-30	4.8%	5.4%	5.2%	5.1%
30-36	3.6%	3.8%	4.1%	3.5%
36-48	5.9%	6.7%	6.1%	5.3%
48- ∞	21.4%	15.0%	18.4%	20.0%
total	100.0%	100.0%	100.0%	100.0%

Regions:
N-E = North-East (Groningen, Friesland, Drenthe, Overijssel and Gelderland)
N-W = North-West (Utrecht, Noord-Holland and Flevoland)
S-W = South-West (Zuid-Holland and Zeeland)
S-E = South-East (Noord-Brabant and Limburg)

Appendix B.

In this appendix, we present the results of maximum likelihood estimates of model type III with the vacancy-unemployment ratio.

variable		coefficient
constant		3.47
ln(AGE)		-1.65
occupation	- general	-0.28
	- industrial	-0.04
	- general services	-0.27
education	- primary	-0.81
	- low	-0.48
	- middle	-0.21
ln(V/U)		0.25
error variance σ^2		0.32

Loglikelihood (* 1000) 1080.499

The overall fit of this model is slightly better than the model with the regional dummy variable. The elasticity of the mean duration of unemployment with respect to the vacancy-unemployment ratio falls from 0.32 to 0.25 when we include the error term. The other parameters of the model are in absolute sense higher than in the exponential model, which is probably due to uncorrelated, unobserved effects. In the case of the original model (with a regional dummy variable), the other parameters are not biased downward in absolute sense in the exponential hazard specification. This could be a consequence of the specification of the regional effect. The regional dummy variable might have taken care of a part of the unobserved effects in the exponential model. Finally note that the degree of heterogeneity is the same as in the original model.

To sum up, a different specification of the regional effect does not significantly change the outcomes of the original model. It does give more insight in the underlying cause of the different regional effects, namely the difference in the relative number of vacancies.

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