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An event history analysis on German long-term unemployment

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Abstract

This paper investigates the determinants of German long-term unemployment. In particular a microeconometric event history analysis will be carried out to examine what impact personal characteristics such as age, gender, education, etc. or factors such as receiving unemployment benefits have on the length of unemployment. The paper further discusses the advantages and disadvantages of a semi-parametric and a parametric estimate of the sample. The use of the Cox model on the one hand and a Weibull specified model on the other have failed to offer any corroboration for application of the semiparametric approach favoured in the theoretical literature. One can also see that not all groups are equally affected by long term unemployment. This is an important finding in terms of economic policy because it sheds light into appropriate policy measures that should be considered to reduce the lenght of time certain groups spend in unemployment.

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1 Introduction

A particular feature of unemployment in Germany is the high degree of long-term unemployment. Whereas in 1971 only 5.3% of unemployed persons had been out of work for over a year, by 1995 this figure had risen to over 33% (Statistisches Bundesamt, 1997).[1] Hence, part of the dramatic rise in the German unemployment rate in recent years can be explained by the fact that people are staying out of work longer. It is therefore necessary to examine unemployment durations more closely, in order to obtain a comprehensive explanation of the phenomenon of unemployment in Germany.

This paper sets out to investigate the risk of remaining unemployed. In particular it will examine what impact individual characteristics, such as age, gender, education etc. or factors such as receiving unemployment benefits and individuals' job-seeking activities, have on the length of unemployment.

A microeconometric event history analysis will serve as an analytical instrument for this. The investigation will further discuss the methods of semi-parametric and parametric estimation, highlighting their advantages and disadvantages. The Cox model frequently used in literature will be compared with a Weibull-specified model.[2]

2 Unemployment duration - theoretical background

According to the International Labour Organization (ILO), someone is unemployed when the person is available and actively seeking for work. This paper will examine how relevant these criteria are in explaining the length of time spent in unemployment. Neoclassical theory commonly assumes that the labour market tends towards equilibrium. This implies both flexibility on the part of workers and the total flexibility of prices and wages. In search theory this Walrasian notion of an ideal market does not longer exist; rather, incomplete information makes it necessary to seek work and therefore to stay out of work. Moreover, the unemployed person weighs the costs of

[1] These figures apply to the former Federal Republic. Initially the figures for East Germany were below the level in the West, but meanwhile they have also topped the 30% mark.

[2] See Wurzel (1993), Steiner and Kraus (1995), Hunt (1995), Steiner (1997) for applications of the Cox approach and Schneider (1990) for a parametric model.

unemployment against the gain of unemployment benefits. This determines the so-called reservation wage at which the job-seeker is willing to take on work. The theory states that the duration of unemployment is determined by the length of time it takes until the unemployed person is offered a job paying higher compensation than the reservation wage.[3] It nonetheless exhibits considerable weaknesses as an explanation for long-term unemployment, since even prolonged periods out of work are perceived as voluntary unemployment.[4]

Another relevant approach to the explanation of long term unemployment is the human capital theory. According to this theory, an individual will continue investing in education until the return on this education offsets the costs. This has two consequences for unemployment duration. First, unemployment is part of the calculated risk when investing in human capital.[5] Second, the longer an individual remains unemployed, the more his human capital is depleted.

3 Data and variables

This analysis uses the Socio-Economic Panel (SOEP) of the German Institute for Economic Research (DIW), with reference to the anual surveys from 1992 to 1996. In each survey people are asked about their occupational status, individual characteristics, education, profession and income. Moreover a particular survey is conducted, in which people are asked retrospectively about their occupational status in each month of the last year. It is possible to generate the variable "duration" from this calendar data, given that the beginning and end of the occupational status "unemployed" are known in each case.

[3]See Ehrenberg and Smith (1996) for details.

[4]See Cox and Schwedler (1997).

[5]This implies that unemployment is voluntary in nature, which does not necessarily appear realistic. Moreover, the "market value" of the on-the-job knowledge which an individual acquires by working is difficult to assess.

Table 1: Censoring

	Frequency	Percentage	Cumulative Percentages
Uncensored	3204	73,2	73,2
R-censored	986	22,5	95,7
L-censored	151	3,4	99,2
L-R-censored	37	0,8	100,0
Total	4378	100,0	100,0

Source: SOEP

3.1 Problems in data use

One problem with use of the data is that the sample is distorted with regard to short durations (length biased sampling, Wurzel, 1993). It may be assumed that people who only expect to be unemployed for a short period are not prepared to spend time registering, and instead look for work on their own without registering.

A further problem of unemployment duration sampling is that some unemployed may have not completed their unemployment spells; the observations are said to be censored. Observations are described as right-censored if the end of the unemployment period is not known while left censoring indicates that the beginning is unknown. In the case of right censoring the limited informative content of the observation can be handled methodically, whereas left-censored data is as a rule removed from the dataset.[6] Table 1 summarizes censoring in the sample.

Another problem arises from the use of calendar data. The survey takes place retrospectively, i.e. the individual is supposed to remember his or her own employment status in the previous year. Research by Bound, Brown, Duncan and Rodgers (1990) has shown that the power of recall is particularly restricted the farther back unemploy-

[6]Right-censored data can be used through particular specification of the likelihood function. But since the inclusion of left-censored data involves highly restrictive assumptions, this data is left out (cf. Schneider (1990)).

ment lies.[7]

Another difficulty with the data arises from the fact that variables can alter in the course of time. It is possible, for example, that people change their family status while unemployed. This problem is eliminated in this study by linking the data on durations from one year with the exogenous variables from the respective year.[8]

4 The econometric model

The analysis is based on a microeconometric model[9], which explains the duration of unemployment with respect to various exogenous variables (co-variables). In contrast to classical multiple regression, it is not assumed that the linear combination $x'\beta$ directly influences the duration T but rather influences a function of T, e.g. $\ln T$ (Blossfeld et al., 1986).

4.1 Central concept of the analysis

The analysis is not based on unconditional probability, e.g. the likelihood that an individual was unemployed for exactly ten weeks, but rather on conditional probability, in other words the likelihood of an individual ceasing to be unemployed, given that he or she was out of work for nine weeks.[10] The unconditional probability of ceasing to be unemployed is given by the hazard rate.[11]

[7] This is also evident in the so-called January/December phenomenon. The data shows that most unemployment began or ended in these months, but this is not substantiated by the actual movements recorded in the statistics from the Federal Labour Office.

[8] One problem here is that the calendar dataset contains people not surveyed in the previous year. But this leads to the loss of only very few observations.

[9] Cf. Kiefer (1988), Blossfeld, Hamerle and Mayer (1986), Yamaguchi (1991) on the methodology.

[10] Of course conditional and unconditional probabilities are different mathematical descriptions for one and the same process. But the use of conditional probabilities is easier to model and economically better to interpret. See Kiefer (1988).

[11] This is not quite correct, since the hazard rate actually refers to conditional densities rather than probabilities and can therefore assume values higher than one.

4.2 The hazard and survivor function

For any specification of the hazard function there exists an equivalent representation of a probability distribution, describing the same system with the same parameters. The probability distribution of the unemployment durations is given by:

$$F(t) = Pr(T < t)$$

The random variable T is smaller than the point on the time interval t. The density function of the durations can be obtained by differentiating the probability distribution $F(t)$.

$$F'(t) = f(t)$$

However, the more interesting concept in terms of the following analysis is the survivor function, which is defined as follows:

$$\begin{aligned} S(t) &= 1 - F(t) \\ &= Pr(T \geq t) \end{aligned}$$

This denotes the likelihood of the random variable T being greater than or equal to the point in time t, in other words of the person remaining unemployed. The hazard function is as follows:

$$\lambda(t) = \frac{f(t)}{S(t)}$$

It describes the rate at which individuals cease being unemployed (or "exit" unemployment), given that they were out of work until t.[12]

4.3 Estimation methods

Now that the hazard rate has been introduced as the central concept, the following section describes the various possibilities of modelling the hazard rate with respect to

[12]The constant time formulation of a sequence of conditional probabilities is then simply the limit:

$$\lambda(t) = \lim_{h \to 0} \frac{1}{h} Pr(t \leq T < t + h | T \geq t)$$

The hazard rate is described by the limit of the conditional probability an individual leaving unemployment in the interval [t,t+h], given the co-variables and that no transition had taken place up to the point in time t.

various co-variables. Essentially, one can distinguish between non-parametric, semi-parametric and parametric methods. The following describes the parametric method and the more commonly used semi-parametric method.[13]

4.3.1 Parametric method

With the parametric method, the assumption is first made that the distribution of unemployment durations can be specified and modelled by a known distribution, such as the exponential distribution[14]. For example:

$$\lambda(t, x, \beta) = e^{x'\beta}$$

Except for one unknown parameter β, the distribution of the data is known. Consequently the density function can be calculated, and from this we can obtain a precisely specified likelihood function in the following form:

$$L^*(\theta) = \prod_{i=1}^{n} f(t, \theta)$$

The likelihood function is the common density function as a function of $\theta = x'\beta$.
In the event of right-censoring the following modification is made:

$$L(\theta) = \sum_{i=1}^{n} d_i \ln f(t_i, \theta) + \sum_{i=1}^{n} (1 - d_i) \ln S(t_i, \theta)$$

with the dummy $d_k = 1$, if the observation is censored or $d_k = 0$ if the observations are uncensored. Using the relationship $f(t_i, \theta) = \lambda(t_i, \theta) S(t_i, \theta)$, one obtains the likelihood function expressed in hazard rates.[15]

4.3.2 Semi-parametric method

The so-called *Cox Proportional Hazard* model is applied as an example of as semi-parametric method. In general a specification of the hazard rate in the following

[13]The nonparametric analysis is useful to display the data on durations and for preliminary analysis on possible functional forms. Nonparametric survivor- and hazard functions can be estimated for the whole sample. A nonparametric analysis however cannot reveal great insights in terms of an explorative analysis on the influence of certain variables on the duration of unemployment. Thus nonparameric methods are not discussed in this paper.

[14]The exponential distribution is a special case of the Weibull distribution

[15]Here we can then insert the assumed functional form of the hazard rate, e.g. $\lambda(\cdot) = e^{x'\beta}$.

functional form is assumed:

$$\lambda(t, x, \beta, \lambda_0) = \phi(x, \beta)\lambda_0(t)$$

with λ_0 as the baseline hazard which corresponds to the hazard rate when $\phi(\cdot) = 1$. Unlike the parametric model, this hazard rate is completely unspecified. The co-variables enter into the hazard rate through the function $\phi(\cdot)$, for which the following form is normally assumed:

$$\phi(x, \beta) = e^{x'\beta}$$

The co-variables therefore have a multiplier effect in the model, shifting the hazard rate in accordance with the magnitude of their influence. This influence is independent of time.[16] With the interpretation of the coefficients as constant, proportional effects on the conditional probability to leave unemployment, the interpretation is quite similar to the linear regression approach. Most importantly the influence of the co-variables can be determined without having specified a probability distribution for the durations.

Estimation with the Cox model is carried out by means of a partial likelihood estimate. In the estimate only the relative influence of the co-variables is of interest. The likelihood function is as follows:[17]

$$L(\beta) = \prod_{i=1}^{n} \frac{\lambda_i(t, x, \beta, \lambda_0)}{\sum_{j>i} \lambda_j(t, x, \beta, \lambda_0)}$$

With the hazard rate given by $\lambda(t, x, \beta,) = \phi(x, \beta)\lambda_0(t)$, one obtains:

$$\frac{\lambda(t_1, x_1, \beta)}{\sum_{i>1}^{n} \lambda(t_1, x_i, \beta)} = \frac{\phi(x_1, \beta)}{\sum_{i>1}^{n} \phi(x_i, \beta)}$$

[16]The coefficients can be interpreted as a constant proportional effect on the conditional likelihood of the duration. With the above specification of the co-variable function we arrive at:

$$\frac{\partial \ln \lambda(t, x, \beta, \lambda_0)}{\partial x} = \frac{\partial \ln \phi(x, \beta)}{\partial x}$$

In the case of $\phi(x, \beta) = e^{x'\beta}$ we find:

$$\frac{\partial \ln \lambda(t, x, \beta, \lambda_0)}{\partial x} = \beta$$

[17]The partial likelihood is obtained by expanding the likelihood function familiar from the parametric methods and ultimately making only the first factor in the function the subject of maximisation. Since β is also contained in the second term, the partial likelihood method leads to a loss of information that can prove particularly problematic in the case of small samples.

One can see that the baseline hazard cancels out. In other words, the likelihood function becomes a pure function of the unknown coefficient vector β. So the functional form of the hazard rate does not need to be specified. The log likelihood function is then as follows:

$$L(\beta) = \sum_{i=1}^{n} \left\{ \ln \phi(x_i, \beta) - \ln \left[\sum_{j>i}^{n} \phi(x_j, \beta) \right] \right\}$$

The log likelihood function is therefore the sum of the conditional probabilities. The fact that an individual for example becomes employed and therefore leaves unemployment defines the "event". This event determines the conditional probability that individual i exits to employment, given that for the remaining persons in the sample the "event" has not occured yet. Hence only the relative order of the durations determines estimation of the unknown parameters.[18]

4.3.3 Advantages and disadvantages of the estimation methods

Both estimation methods have advantages and disadvantages. The advantage of the Cox model frequently mentioned in the literature is the unspecified hazard rate.[19] This means that the durations do not have to be based on any particular distribution, enabling an extremely flexible estimate. Another advantage is that the estimated coefficients can be meaningfully interpreted as elasticities.

A disadvantage, however, is that the Cox model uses only the relative order of durations for the estimate rather than precise durations. This results in a loss of information, particularly with small samples (Yamaguchi, 1991). Moreover, if the variables are time dependent, i.e. if the influence on the unemployment duration varies over time, the assumptions of the Cox model would be violated.

The more restrictive assumptions, however, are made in the parametric model. By this method an exact distribution is assumed for the durations, which can be interpreted as an advantage as well as a disadvantage. Additional assumptions are made on the duration dependence of the hazard rate, which can occasionally be implausible. On the other hand, the estimate is very efficient, since the exact durations with a specified distribution are used.

[18] Cf. Yamaguchi (1991)

[19] Cf. Blossfeld et al. (1986)

Table 2: Average Duration (in months)

	Total	Men	Women
Mean	8,84	7,89	9,86
Minimum	1	1	1
Maximum	60	60	58

Source: SOEP

5 Descriptive statistics and regression results

The average duration of unemployment of the people in the sample is shown in Table 2. We can see that women remain unemployed for almost 10 months on avarage, while men are unemployed on avarage for only 8 months.[20]

The following estimation is based on a competing risk model, i.e. the transitions between unemployment and two target situations are examined. People can either move into employment or economic inactivity. Looking at Table 3, we can see that men and women exit into the respective target situations with differing frequency. It is striking that women exit more often than men into part-time work and occupational training. When the change is to economic inactivity, more men than women exit into retirement and fewer into housework.

On the basis of a competing risk model, the analysis was conducted separately for men and women to determine whether there are any significant gender-related differences in the influences on the hazard rate for the respective target situation. The following covariables were included in the analysis: age, health, disability, family status, dismissal by the employer, future job perspectives, educational attainment, university degree, no occupational training, education from East Germany and receiving unemployment benefits. Table 4 shows the labels of the dummy-variables used in the regressions.

The model was estimated both semi-parametrically (see Table 5) according to the Cox approach and parametrically (see Table 6) with a Weibull specified distribution of un-

[20]This is also confirmed by the survivor functions gained from the estimate.

Table 3: Exits from unemployment by event

	Total	Percentage	Men	Women
Full employment	1820	61,7	1151	669
Temporary Layoff	9	0,3	3	6
Part-time	280	9,5	40	240
Training	353	12,0	127	226
Retirement	137	4,6	83	54
Maternity Leave	72	2,4	0	72
School/University	72	2,4	41	31
Military/Civil Service	39	1,3	39	0
Housewife/man	63	2,1	3	60
Others	61	2,1	36	25
Missing Values	45	1,5	23	22
Total	2951	100,0	1546	1405

Source: SOEP

employment durations.[21] In addition, an estimate of the full sample with a single risk model was carried out using the parametric method, i.e. no differentiation was made according to gender or target situations (see Table 7).[22]

With regard to the gender-specific factors the competing risk estimation reveals two interesting differences between men and women (see Table 5 and 6). The coefficient of the variable "family status" shows that married women face a higher risk to exit into economic inactivity while married men have greater chances to return into employment. This shows that the mere fact of being married has a significant positive effect on the likelihood of leaving unemployment. Note, however, that women are forced into economic inactivity which only reduces long term unemployment statistically. The variable "education from East Germany" seems to have a significant negative impact

[21]Estimates with other distributions produced similar estimate results. The motivation for using the Weibull distribution was that its density function tallied rather well with the histogram of durations.

[22]To check the quality of the models a likelihood ratio test was carried out, which exhibited significant values for all models.

Table 4: Dichotomous Variables, Labels

Variable	Label	
Sex	0: female	1: male
Health condition	0: not good	1: good
Disability	0: no	1: yes
Family status	0: not married	1: married
Dismissal by employer	0: no	1: yes
Job perspectives	0: pessimistic	1: optimistic
University degree	0: no degree	1: degree
No training	0: no	1: yes
Education East	0: no	1: yes
Unemployment benefits	0: no benefits	1: receiving benefits

Source: SOEP

on the employment perspectives particularly for women (see Table 5 and 6).[23] In general, gender differences are shown by the variable "sex" in the full sample estimation (Table 7). If the variable takes the value one, i.e. it is a male person, then it has a significant positive influence on the probability to exit unemployment.

As it is to be expected, age has a negative impact on the probability of men and women leaving unemployment, irrespective of the target situation. It is more difficult for older persons to find a job and therefore increases their duration of unemployment. Health impediments do not appear to constitute a clear risk factor, as they do not show any significant influence.[24] In the full sample analysis the variable "disability" is negatively significant, but does not show any significant impact in the competing risk estimation. The variable "dismissal by the employer" was included to reflect the reason for unemployment and its impact on the re-employment chances. One would expect persons

[23]This could be explained by the fact that women from Eastern Germany had a higher labor market participation rate and in the course of the structural change triggered by German reunification they now run a greater risk of becoming unemployed and then remaining out of work. This theory needs to be examined more closely, as the variable could also reflect other East German influences.

[24]It must be said here that this variable is based on the interviewees' subjective assessments of their own well-being. The scale of 1-5 was transformed into a dichotomous dummy, which probably makes the variable even less powerful.

being dismissed by the employer to be longer unemployed than persons leaving their job voluntarily to seek for a better job. Indeed, the results more or less show a significant negative influence of the variable on the hazard rate, i.e. the conditional probability leaving unemployment (see Table 6 and 7).

The education variable conveys serious difficulties. The variable only indicates the type of highschool degree from the German school system and is therefore not able to indicate further educational attainment like college education or other specific training. The variable further neglects to take into consideration such factors as on-the-job know-how and professional work experience, which lead to an inaccurate estimate of a person's job perspectives.[25] The negative sign of the coefficient casts doubt on the quality of the variable since one would expect a positive relationship between education and the likelihood of leaving unemployment.[26]

To get a clearer picture on the impact of education on an individual's duration of unemployment two further variables were included in the analysis. Possession of a university degree, i.e. if the dummy variable "university degree" takes the value one, has a positive influence on the hazard rate and thus increases the probability to leave unemployment. On the other hand the failure to complete occupational training increases the risk of remaining unemployed.

The variables "personal job perspectives" and "job search" were considered to evaluate an unemployed person's motivation and commitment to find a job (see Table 7). For the variable "job search" persons were asked whether they had looked for work in the past three months. The "job-search" variable, however, was included only for two anual surveys, which casts doubt on its informative value. It had a significantly positive effect only for men exiting to employment, i.e. men actively searchimng for work tend to leave unemployment faster than men who do not search for work.[27] Due

[25]The existence of segmented labour markets can also distort the impact of education (cf. Lutz and Sengenberger (1974).

[26]A better way of modelling education would have been to employ a metric variable "years of education". However the SOEP provides this variable not for all observations and therefore would have reduced the sample significantly.

[27]The variable should not be over-emphasized, given that only persons registered as unemployed are considered here, most of whom are placed by the Federal Labour Office, in which case they do not actively seek work.

to the many missing values, it was not included in the full sample estimate.[28]
The variable "receiving unemployment benefits" shows mixed evidence. While the estimation of the single risk model in Table 7 reveals that receiving unemployment benefits has a significant negative impact on the probability to exit unemployment, in the estimation of the competing risk model (Table 5 and 6), however, the variable seems to be significant only for men leaving unemployment for employment and women exiting to economic inactivity.

6 Parametric vs. semi-parametric methods

We see from the estimate using the Cox model that comparatively few significant values are shown. The reason for this may lie in the disadvantages of the Cox approach previously discussed.[29] Particularly with the separate assessment of target situation and gender, the loss of information caused by considering only relative relations may be substantial. In addition, the variables may be time-sensitive, which would also impair the assumptions of the Cox model.
In contrast, the Weibull model generates a "good" estimate, which can be explained by the efficiency gain due to the distribution assumption.[30] On the other hand, the Weibull model assumes a slightly rising hazard function, which is disputed in theoretical literature.[31] On the one hand it appears implausible that the likelihood of exiting unemployment should rise the longer the individual is out of work. Yet on the other one can imagine that once their unemployment benefits are no longer paid, the unemployed do make greater efforts to seek work, which would at least explain a rising hazard function in the latter time intervals.

[28]According to Engel and Pötschke (1997), the exclusion of missing values can severely reduce the sample and thus lead to efficiency-reducing estimates. Moreover, a systematic correlation could exist between non-response and the relevant variable.

[29]Of course the model may also be wrongly specified through the choice of co-variables.

[30]As already mentioned, the distribution assumption seems to be plausible (see footnote 21). Under these conditions a parametric model generates a more efficient estimate than a semi-parametric approach.

[31]The longer the unemployment, the fewer observations are included in the estimate, which is why a slight increase should not be over-estimated.

7 Concluding remarks and summary

With regard to the questions raised in the introduction, the following conclusions can be drawn. This paper has been able to show that job-seeking activity and availability as explanations of unemployment duration are important only to a limited extent. The reservation wage theory has been partly confirmed. The variable ”required reservation wage” was highly significant after its inclusion in the model. Yet it must be said that the variables ”available household income” and ”amount of unemployment benefit” do not produce any improvement in the quality of the models and did not significantly contribute to an explanation.

For the human capital theory, too, the estimates provide only mixed evidence. The education variables are presumably unable to depict the theoretical concept of ”investment in human capital” as such.

The so-called ”problem group variables”, such as age, disability and gender, have the anticipated impact. One can see that not all groups are equally affected by long-term unemployment. This is an important finding in terms of economic policy because it sheds light into appropriate policy measures that should be considered to reduce the lenght of time certain groups spend in unemployment.

The use of the Cox model on the one hand and the Weibull model on the other have failed to offer any corroboration for application of the semi-parametric approach favoured in the theoretical literature. Because the Weibull model has proved to adjust well to the data, it is therefore not a disadvantage to specify the distribution of the hazard function.

Table 5: Estimation of a competing risk model

	Semi-parametric estimation: Cox model			
	Men-employm.	Men-inact.	Women-employm.	women-inact.
Age	-0,014	-0,038	-0,011	-0,029
	(-4,19)**	(-5,86)**	(-2,94)**	(-4,43)**
Health	-0,039	-0,019	-0,078	0.004
	(-0,60)	(-0.108)	(-0,012)	(0.025)
Disability	-0,10	-0,32	-0,15	-0,081
	(-0,71)	(-1,38)	(-0,69)	(-0,31)
Family status	0,32	-0,12	-0,044	0,37
	(4,32)**	(-0,57)	(-0,58)	(2,13)**
Dismissal	-0,070	-0,19	-0,22	-0,40
	(-0,97)	(-0,79)	(-2,36)**	(-1,81)
Job perspectives	0,28	0,41	-0,004	0,25
	(2,15)**	(1,49)	(-0,02)	(0,79)
Education	0,017	0,14	-0,025	0,068
	(0,27)	(1,09)	(-0,29)	(0,39)
University degree	0,018	1,3	0,21	-0,12
	(0,14)	(2,10)**	(1,39)	(-0,29)
No training	-0,063	-0,87	-0,099	0,12
	(-0,82)	(-2,20)**	(-1,09)	(0,71)
Education East	0,055	-0,53	-0,22	-0,11
	(0,817)	(-2,77)**	(-2,91)**	(-0,72)
Unempl.-benefits	-0,064	0,67	0,16	0,35
	(-0,99)	(0,38)	(2,42)	(2,30)**

Note: t-values in parenthesis with ** - significant at the 5% Level,
* - significant at the 10% Level

Table 6: Estimation of a competing risk model

	Parametric Estimation: Weibull model			
	Men-employm.	Men-inact.	Women-employm.	Women-inact.
Age	-0,042	-0,041	-0,037	-0,044
	(-18,4)**	(-8,57)**	(-17,2)**	(-11,5)**
Health	-0,002	-0,031	-0,018	-0.080
	(-0,04)	(-0.25)	(-0,316)	-(0.58)
Disability	-0,058	-0,20	-0,10	-0,073
	(-0,46)	(-0,88)	(-0,53)	(-0,28)
Family status	0,48	-0,047	0,048	0,37
	(8,15)**	(-0,24)	(0,76)	(2,64)**
Dismissal	-0,21	-0,14	-0,30	-0,29
	(-3,53)**	(-0,78)	(-3,317)**	(-1,39)
Job perspectives	-0,019	0,30	-0,38	-0,41
	(-0,21)	(0,13)	(-2,97)**	-(1,44)
Education	-0,33	-0,16	-0,47	-0,58
	(-7,47)**	(-1,47)	(-8,20)**	(-4,78)**
University degree	0,21	1,17	0,42	(0,16)
	(2,10)**	(1,28)	(3,07)**	(0,47)
No training	-0,40	-0,62	-0,41	-0,21
	(-6,94)**	(-5,73)**	(-6,11)**	(-1,77)*
Education East	0,056	-0,70	-0,40	-0,42
	(0,96)	(-6,11)**	(-6,32)**	(-3,43)**
Unempl.-benefits	-0,22	0,23	0,37	0,21
	(-3,97)**	(0,16)	(0,60)	(1,47)

Note: t-values in parenthesis with ** - significant at the 5% Level,
* - significant at the 10% Level

Table 7: Estimation of a single risk model

	Parametric Estimation: Weibull model			
	Total	Total	Women	Men
Age	-0,049	-0,045	-0,048	-0,049
	(-32,31)**	(-11,69)**	(-23,90)**	(-24,07)**
Sex	0,12	0,27	-	-
	(3,51)**	(3.27)**	-	-
Health	-0,048	-0,087	-0,082	-0.013
	(-1,24)	(-1,06)	(-1,49)	-(0.25)
Disability	-0,15	-0,19	-0,18	-0,18
	(-1,73)*	(-1,15)	(-1,24)	(-1,77)*
Family status	0,12	0,10	0,092	0,23
	(3,17)**	(1,33)	(1,59)	(4,13)**
Dismissal	-	-0,34	-	-
	-	(-4,08)**	-	-
Job perspectives	-0,052	0,18	-0,21	0,024
	(-0,69)	(1,88)*	(-1,55)	(0,28)
Reservation wage	-	-0,0003	-	-
	-	(-6,99)**	-	-
Education	-0,33	-0,25	-0,35	-0,27
	(-10,46)**	(-3,32)**	(-6,93)**	-(6,78)**
University degree	0,34	0,77	0,32	0,31
	(4,32)**	(4,31)**	(2,54)**	(3,05)**
No training	-0,63	-0,64	-0,69	-0,55
	(-14,95)**	(-7,02)**	(-11,59)**	(-9,26)**
Education East	-0,25	-0,32	-0,42	-0,029
	(-8,04)**	(-4,72)**	(-9,14)**	(-0,74)**
Unempl.-benefits	-0,35	-0,27	-0,20	-0,46
	(-9,43)**	(-3,50)**	(-3,93)**	(-8,64)**
Observations	3222	833	1524	1698

Note: t-values in parenthesis with ** - significant at the 5% Level,
* - significant at the 10% Level

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