

An Empirical Study on Canadians' Unemployment Duration

By

Baomin Dong

Department of Economics

Concordia University

Montreal, Quebec,

H3G 1M8 Canada

1. Introduction

Unemployment is the main concern in post-war labor economics literature. It is defined as the non differential of labor resources as a result of which the actual output of the economy is below its potential GNP. To overcome the problem of unemployment which caused by changes in demand patterns and/or supply side deficiencies, existing various policy measures may be adapted. The usefulness of such policies depends on the reliability of the predictions made by the economic theory. To make the prediction robust, not only accurate information about the characteristics of the unemployment is required, likelihood function must be carefully and correctly constructed also. In this study, duration method is applied in which the length of unemployment spells play a crucial role. Average unemployment duration will be used for statistical purpose since the unemployment rate is less meaningful for our purpose of study. The structure of this paper follows. In section 2, we introduce the models of duration data, in section 3, we derive several commonly used parametric duration models, in section 4 we give the likelihood function of duration model and maximum likelihood estimation method, in section 5 and 6 we deal with the heterogeneity, section 7 and 8 deal with the data and estimation and offer some conclusions.

2. Models of duration data

There are different models regarding the econometric analysis of duration data. To apply familiar inference techniques and provide a convenient departure, we will focus most of our attention on what is known as parametric models. To set up the theoretical framework of these models, we start by introducing a few straightforward concepts, less complicated techniques and applications in duration data.

While labor economists were not interested in unemployment duration until recently, engineers have studied the timing of failure for decades. In duration framework, the variable of interest in the analysis of duration is the length of time that elapsed from the beginning of some events either till their ends or till the measurement is taken, which

$$t_1, t_2, \Lambda, t_n.$$

may precede termination. Observations will typically consist of a cross section of duration,

The process being observed may have begun out different points in calendar time.

In the analysis of duration data, censoring is a pervasive and unavoidable problem. The common cause to that the measurement is made while the process is ongoing. For instance, information on the length of unemployment is collected only on those individuals unemployed at the time of the survey. This means that time spent on unemployment will not be computed for those individuals employed at the time of each close monthly survey, but unemployment between surveys.

Models for duration data is quite different from the conventional regression model. The labor models that characterize the conditional mean and variance of a distribution, the regressors can be taken as fixed characteristics at the points in time or for the individual for which the former model the observation is implicitly on a process that has been under way for a length of time, $t = (0, t)$. If the analysis is conditioned on a set of covariates X , the duration is implicitly a function of the entire path of such variables which may have changed during the interval. Variables that one would like to account for in the duration of unemployment; therefore, the treatment of time varying covariates is a considerable complication.

3. Parametric Models of Duration

In these models we will use spell as a catchall for different duration variables we might measure. Spell length is given by the random variable T . A simple approach to duration analysis would be to apply regression analysis to the observed spells. By this means, we could characterize the expected duration, perhaps conditioned on a set of covariates whose values were measured at the end of the period. We could assume also that conditioned on an X which has remained fixed from $T = 0$, to $T = t$, where t has a normal distribution, as we usually do in regressions. However normality of t turns out not to be particularly attractive in this setting for a variety of reasons, not least of which is that

duration is positive by construction, while a normally distributed variable can take negative values. Thus there are different alternatives like heterogeneity.

Suppose that spell length T has a continuous probability distribution, $f(t)$ where t is a realization of T . The cumulative probability is

$$F(t) = \int_0^t f(s)ds = \Pr(T \leq t),$$

We are more interested in the probability that the spells whose length is at least t , which is given by the survival function,

$$S(t) = 1 - F(t) = \Pr(T \geq t),$$

Which is the probability that the spell will end in the next short interval of time, given that it has lasted till time t .

Another useful function for characterizing this aspect of the distribution is the hazard rate,

$$\begin{aligned} \mathbf{I}(t) &= \lim_{\Delta \rightarrow 0} \frac{\Pr(t \leq T \leq t + \Delta \mid T \geq t)}{\Delta} \\ &= \lim_{\Delta \rightarrow 0} \frac{F(t + \Delta) - F(t)}{\Delta S(t)} = \frac{f(t)}{S(t)}, \end{aligned}$$

The hazard rate is roughly the rate at which spells are completed after duration t , given that they lasted at least till t . As such, the hazard function gives an answer to our question. So we may prefer to model the hazard function rather than the density, CDF, or

$$\mathbf{I}(t) = \frac{-d \ln S(t)}{dt},$$

$$f(t) = S(t)\mathbf{I}(t),$$

survival function. It is easy to show that

The integrated hazard function is defined below,

$$\Lambda(t) = \int_0^t \mathbf{I}(t)dt$$

for which

$$S(t) = e^{-\Lambda(t)},$$

So, $\dot{\Lambda}(t) = -\ln S(t),$

Based on the results above, we may consider modeling the hazard function directly, rather than the survival function, then for purposes of estimation, integrating backward to obtain the density. The base case for many analyses is a hazard rate that does not vary over time, that is, $\mathbf{I}(t)$ is a constant, \mathbf{I} . This is a characteristics of a process that has no memory. The conditional probability of failure in a given short interval is the same regardless of when the observation is made. Thus,

$$\mathbf{I}(t) = \mathbf{I}$$

from the earlier definitions, we obtain the simple differential equation,

$$\frac{-d \ln S(t)}{dt} = \mathbf{I}(t),$$

The solution is,

$$\ln S(t) = k - \mathbf{I}t,$$

or,

$$S(t) = ke^{-\mathbf{I}t},$$

where k is the constant of integration. The condition that $S(0) = 1$ implies that $k = 1$, and the solution is

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

This is the exponential duration specification, which has been used to model the timing for failure of the electronic components, precisely because of the memoryless property of the distribution. Estimation of \mathbf{I} is simple, since with an exponential distribution,

$E(t) = 1 / \mathbf{I}$. The maximum likelihood estimate of \mathbf{I} will be

$$1/\tilde{t}.$$

A natural extension is to model the hazard rate as a linear function.

$$\mathbf{I}(t) = \mathbf{a} + \mathbf{b}t,$$

then

$$\mathbf{I}(t) = \mathbf{a}t + (1/2)\mathbf{b}t^2,$$

and

$$f(t) = \mathbf{I}(t) S(t) = \mathbf{I}(t) \exp [-\mathbf{I}(t)],$$

With an observed sample of duration, estimation of \mathbf{a} and \mathbf{b} is, at least in principle, a straightforward problem in maximum likelihood.

A distribution whose hazard function slopes upward is said to have positive duration dependence. For such distributions, the likelihood of failure at time t , conditional upon duration up to time t , is increasing in t . The opposite case is that of decreasing hazard or negative duration dependence. The duration of unemployment spells can be framed in terms of positive or negative duration dependence and depends whether the data can be characterized by positive or negative duration dependence, it is counterproductive to assume a distribution that displays one characteristic or the other over the entire range of t . Thus, the exponential distribution of our suggested extension could be problematic.

The literature contains a multitude of choices for duration models, including normal, inverse normal, log-normal, F, gamma, Weibull and many others. The following lists the hazard functions and survival functions for four commonly used distributions.

Exponential: hazard rate does not vary over time.

$$\lambda(t) = \lambda$$

$$S(t) = e^{-\lambda t},$$

Weibull:

$$\lambda(t) = \lambda p(\lambda t)^{p-1},$$

$$f(t) = \mathbf{g} \mathbf{a} t^{\mathbf{a}-1} \exp(-\mathbf{g} t^{\mathbf{a}})$$

$$S(t) = e^{-(\lambda t)^p},$$

Log-normal:

$$f(t) = (p/t) \mathbf{f}(p \ln(\lambda t)),$$

where $\ln t \sim N(-\ln \lambda, 1/p)$

$$S(t) = \Phi(-P \ln(\lambda t)),$$

Logistic:

$$\lambda(t) = [\lambda P(\lambda t)^{p-1}] / [1 + (\lambda t)^p],$$

$$S(t) = 1 / (1 + (\lambda t)^p),$$

As we can see, the hazard function for exponential distribution is constant and for Weibull is monotonically increasing or decreasing on p , and the hazards for log-normal and log-logistic distributions increase first and then decrease. Which among these or the many alternatives is likely to be the best in any application is uncertain.

4. Maximum Likelihood Estimation

From the Tobit analysis on the censored regression model, we get the likelihood.

Consider for censored data,

$$y_i^* = \mathbf{b}' \mathbf{x}_i + \mathbf{e}_i,$$

$$y_i = 0 \quad \text{if} \quad y_i^* \leq 0,$$

$$y_i = 1 \quad \text{if} \quad y_i^* > 0.$$

The log likelihood of the censored normal distribution regression model above is,

$$\ln L = \sum_{y_i > 0} -\frac{1}{2} [\ln(2\mathbf{p}) + \ln \mathbf{s}^2 + \frac{(y_i - \mathbf{b}' \mathbf{x}_i)^2}{\mathbf{s}^2}] + \sum_{y_i = 0} \ln [1 - \Phi(\frac{\mathbf{b}' \mathbf{x}_i}{\mathbf{s}})].$$

Similarly, the parameters \mathbf{I} and p of those duration models can also be estimated by the maximum likelihood. Censored observations can be incorporated exactly as in the Tobit model. Therefore,

$$\ln L = \sum_{\text{uncensored observations}} \ln f(t | \mathbf{q}) + \sum_{\text{censored observations}} \ln S(t | \mathbf{q}),$$

Where $\mathbf{q} = (\mathbf{I}, p)$. The log-likelihood function can be also formulated in terms of

$f(t) = \mathbf{I}(t) S(t)$, so that,

$$\ln L = \sum_{\text{uncensored observations}} \mathbf{I}(t | \mathbf{q}) + \sum_{\text{all observations}} \ln S(t | \mathbf{q}),$$

inference about the parameters can be done in the usual way. Either the BHHH estimator or actual second derivative can be used to estimate asymptotic standard errors for the estimates.

5. Exogenous variables

One limitation of the models given above is that external factors do not give a role in the survival distribution. The addition of "covariate" to duration models is fairly straightforward, although the interpretation of the coefficients in the model is less so. For example, consider the Weibull model, let

$$\mathbf{I}_i = e^{-bX_i},$$

where X_i is a constant form and a set of variables which are assumed not to change from time $T = 0$ to the "failure time", $T = t$. Making \mathbf{I} a function of a set of regressors is equivalent to changing the limits of measurement on the time axis. For this reason, these models are sometimes called "accelerated failure time" models.

Note, as well, that in all of the models listed, the regressors do not bear on the question of duration dependence, which is a function of p . Let

$$\mathbf{d} = 1/p,$$

$$d_i = 1, \text{ if the spell is complete,}$$

$$d_i = 0, \text{ if it is censored.}$$

$$w_0 = p \ln(\mathbf{I}, t) = [\ln t_i - \mathbf{b}' x_i] / \mathbf{d}$$

By making the change of variables, we find that

$$F(w_i) = (1/\mathbf{d}) \exp(w_i - e^{w_i}),$$

$$S(w_0) = \exp(-e^{w_0}),$$

The log-likelihood is

$$\ln L = \mathbf{S}[d_i \ln(w_i) + (1 - d_i) \ln S(w_i)],$$

which could be reduced to

$$\ln L = \sum [d_i (w_i - \ln \mathbf{d}) - e^{w_i}],$$

The derivations are obtained by using $\partial w_i / \partial \mathbf{d} = -w_i / \mathbf{d}$ and $\partial w_i / \partial \mathbf{b} = -x_i / \mathbf{d}$. The individual terms can also be used from BHHH estimates of the asymptotic covariance matrix for the estimates. The Hessian is also simple to derive, so Newton's method could be used instead.

Note that the hazard function generally depends on t , p and x . The sign of the estimated coefficients suggest the direction of the effect of the variable on the hazard function when the hazard is monotonic. But in those cases, such as the log-logistic, in which the hazard is non-monotonic, even this may be ambiguous. The magnitude of the effects may also be difficult to interpret in terms of the hazard function. However, in a few cases, we do get a regression-like interpretation. In the Weibull and exponential models,

$$E(t | x_i) = \exp(p \mathbf{b}' \mathbf{x}_i),$$

In these cases, \mathbf{b}_k is the derivative (or a multiple of the derivative) of this conditional mean.

6. Heterogeneity

The problem of heterogeneity in duration models can be viewed essentially as the result of an incomplete specification. Individual specific covariates are intended to incorporate observation specific effects. But if the model specification is incomplete, and systematic individual differences in the distribution remain after the observed effects are accounted for, then inference based on the improperly specified model is likely to be problematic. We have already encountered several settings in which the possibility of heterogeneity mandated a change in the model specification, the fixed and random effects of regression, logit and probit models all incorporate observation-specific effect. Indeed, all of the failures of the linear regression model discussed in the preceding sections can be interpreted as a consequence of heterogeneity arising from an incomplete specification.

There are a number of ways of extending duration models to account for heterogeneity. The strictly non-parametric approach of the Kaplan-Meier estimator is largely immune to the problem, but it is also rather limited in how much information can be called from it.

One direct approach is to model heterogeneity in the parametric model. Suppose that we posit a survival function conditioned in the individual specific effect, v_i .

We treat the survival function as $S(t_i | v_i)$. Then add to that a model for the unobserved heterogeneity, $f(v_i)$. (Note that this is a counterpart to the incorporation of a disturbance in a regression model). Then,

$$\begin{aligned} S(t) &= E_v [S(t/v)] \\ &= \int_0^\infty f(v) S(t/v) dv, \end{aligned}$$

The gamma distribution is frequently used for this purpose. Consider, for example, using this device to incorporate heterogeneity into the Weibull model we used earlier. As is typical, we assume that v has a gamma distribution with mean 1 and variance $\mathbf{q} = 1/k$.

$$f(v) = \frac{k^k}{\Gamma(k)} e^{-kv} v^{k-1},$$

and

$$S(t) = \int_0^\infty f(v) S(t | v) dv = [1 + \mathbf{q}(\mathbf{I}t)^p]^{-1/\mathbf{q}},$$

Then,

The limiting value, with $\mathbf{q} = 0$, is the Weibull survival model, so $\mathbf{q} = 0$ corresponds to $\text{Var}(v) = 0$, or no heterogeneity. The hazard function for this model is

$$\mathbf{I}(t) = \mathbf{I}p(\mathbf{I}t)^{p-1} [S(t)]^{\mathbf{q}},$$

which shows the relationship to the Weibull model. This approach to parametric modeling of heterogeneity tends to over-parameterize the survival distribution and can lead to rather serious errors in inference. This argument is pointed out by Heckman and Singer. Indeed, they also expressed some concern that researchers tend to choose the distribution of heterogeneity more on the basis for mathematical convenience than on any sensible economic basis.

7. The Data

The survey was taken in 1990. Sample size is 2029 and the samples are those who were permanently laid-off from a full job and were not a full-time student. 23 variables are listed for each sample. They are,

Age dummies:

Age1=1 for those who were aged between 16-19 in 1990

Age2=1 for those who were aged between 20-24 in 1990

Age3=1 for those who were aged between 25-34 in 1990

Age4=1 for those who were aged between 35-44 in 1990

Age5=1 for those who were aged between 45-54 in 1990

Age6=1 for those who were aged 55 or above in 1990

Sex =1 for male and 0 for female.

Married =1 for those who were married in 1990, 0 otherwise.

Education dummies:

Edu1=1 for those whose education is less than high-school

Edu2=1 for those whose education is high-school

Edu3=1 for those who had some post-secondary

Edu4=1 for those who had a university degree

Edu5=1 for those who had a trade certificate or diploma

Kid: number of young children aged 5 or below in 1990

Hourly UI benefit:

those who reported being recipient of UI benefit in 1990, who worked more than 10 weeks before being laid-off, and worked more than 20 hours per week.

Maximum insurable earnings in 1990 were \$640 per week, which gives a maximum UI of \$384 per week. Hourly UI benefit were constructed as 60% of hourly wage rate with a maximum of \$10. (Assuming average hours worked per week was 38.4)

Duration of previous job:

Stop week of last job minus start week of that job.

Wage1: hourly wage rate paid on last job.

Search: = 1 if reported wanting and looking for job after being laid off.

Censor indicator: = 1 if unemployment spell was completed, 0 censored.

Unemployment duration: Start week of re-employment minus stop week of last job for completed spell, or week 4696 (last week of January 1991) minus stop week of last job.

Wage2: hourly wage rate of new job found. Missing for censored spell.

SIC: standard industry code of the previous job.

SOC: standard occupation code of the previous job.

8. Estimation and Conclusion

First, we run the regression within Weibull specification on constant, education level variables, marital status and search effort without considering heterogeneity, using LIMDEP. The estimated coefficients and their test statistics are listed below.

Variable	Coefficient	Std. Error	t-ratio	Prob.	Mean & S.D. of Var.	
Constant	7.5016	0.6700	11.196	0.0000		
E2	-0.59833E-01	0.2332	-0.257	0.7975	0.1531	0.3605
E3	-0.92575	0.3231	-2.865	0.0042	0.1137	0.3178
E4	0.14208E-01	0.4006	0.035	0.9717	0.0186	0.1351
E5	-0.51936	0.2224	-2.335	0.0195	0.1763	0.3815
MARI	-0.28753	0.1887	-1.524	0.1275	0.6381	0.4811
SEARCH	-4.8325	0.6343	-7.618	0.0000	0.3202	0.4671
Sigma	0.93557	0.8316E-01	11.250	0.0000		

As we can see, those who had a university degree seems to suffer a longer unemployment duration while those who had some post-secondary education have a shorter duration. Those who married have a shorter duration. And those who were reported wanting and looking for job after being laid off have much shorter duration, in other words, those who paid more effort on job hunting will have a new job much sooner after being laid off from the previous job.

The estimated parameters of the model are listed below.

Parameter	Estimate	Std. Error	Confidence Interval	
Lambda	0.00383	0.00161	0.0007 to	0.0070
P	1.06887	0.09501	0.8827 to	1.2551
Median	185.35192	78.00074	32.4705 to	338.2334

Then we run the regression with heterogeneity allowed, and considering age, gender, the number of the children and industry. The model is still Weibull and heterogeneity is

assumed follows gamma distribution as we derived earlier. The estimated coefficients and parameters of the model are listed below.

Maximum Likelihood Estimates

Variable	Coefficient	Std. Error	t-ratio	Prob.	Mean & S.D. of Var.	
Constant	3.7445	0.7367	5.083	0.0000		
A2	0.18543E-01	0.6145	0.030	0.9759	0.1903	0.3930
A3	-0.13404	0.6068	-0.221	0.8252	0.2993	0.4585
A4	0.17546	0.6110	0.287	0.7740	0.2668	0.4428
A5	-0.10144E-01	0.6224	-0.016	0.9870	0.1508	0.3583
A6	0.83122	0.7162	1.161	0.2458	0.0650	0.2468
SEX	-0.62265	0.2206	-2.823	0.0048	0.6125	0.4877
E2	0.28729	0.2891	0.994	0.3204	0.1531	0.3605
E3	0.29863E-01	0.2925	0.102	0.9187	0.1137	0.3178
E4	-0.67356	0.5214	-1.292	0.1964	0.0186	0.1351
E5	-0.26870	0.2276	-1.181	0.2377	0.1763	0.3815
KID	0.37945	0.1776	2.136	0.0326	0.2552	0.5905
INDUS	0.11384E-01	0.7001E-02	1.626	0.1039	31.6937	13.7279
Theta	0.58168E-06	0.6274	0.000	1.0000		
Sigma	1.1242	0.1841	6.105	0.0000		

Parameter	Estimate	Std. Error	Confidence Interval	
Lambda	0.02084	0.00720	0.0067 to	0.0350
P	0.88955	0.14571	0.6040 to	1.1751
Median	31.78481	10.98547	10.2533 to	53.3163

With more and different variables considered, we got different signs on some of the estimated coefficients. University educated people will have a shorter duration under this specification. Men seemed to be easier to get a new job than women in the job market. Those who had more children will suffer longer duration. And for those who were between 24 to 35 get their new jobs most easily and those who were 55 or above get their new jobs hardest. However, test statistics show that age dummies are not significant.

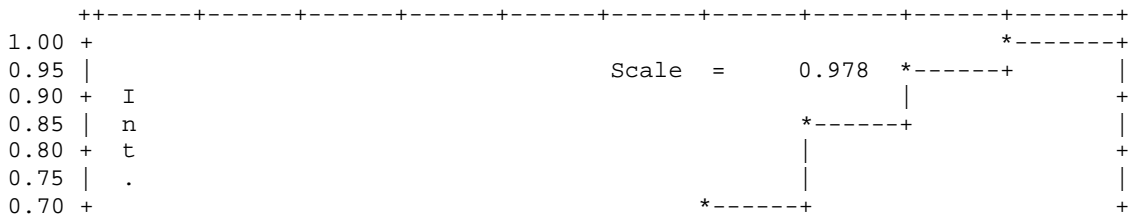
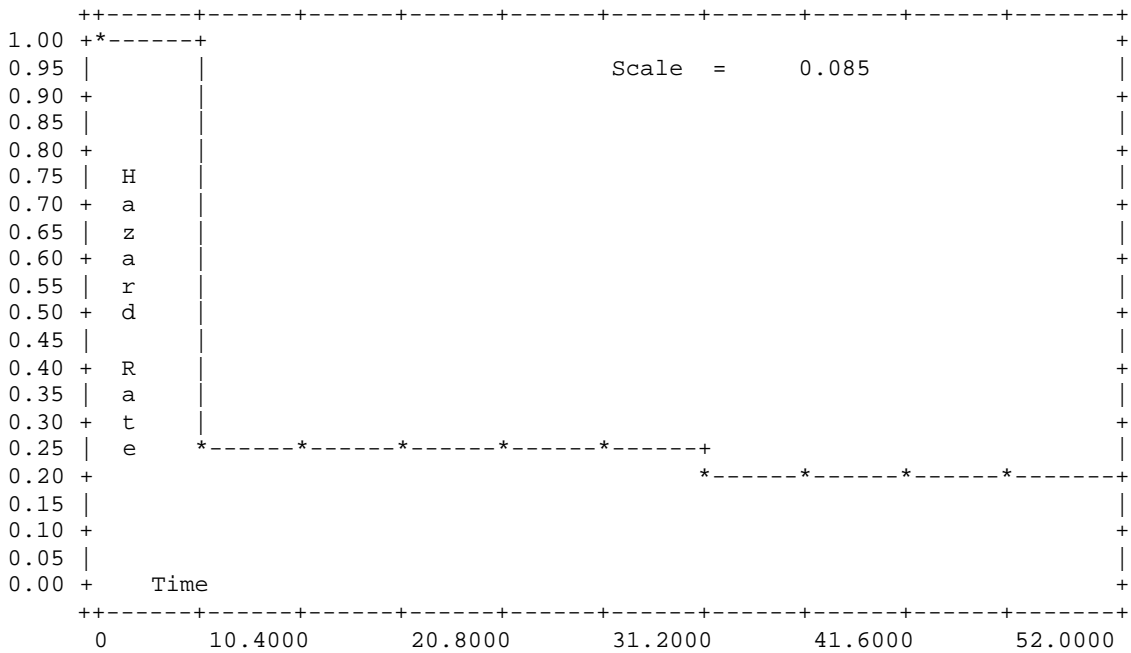
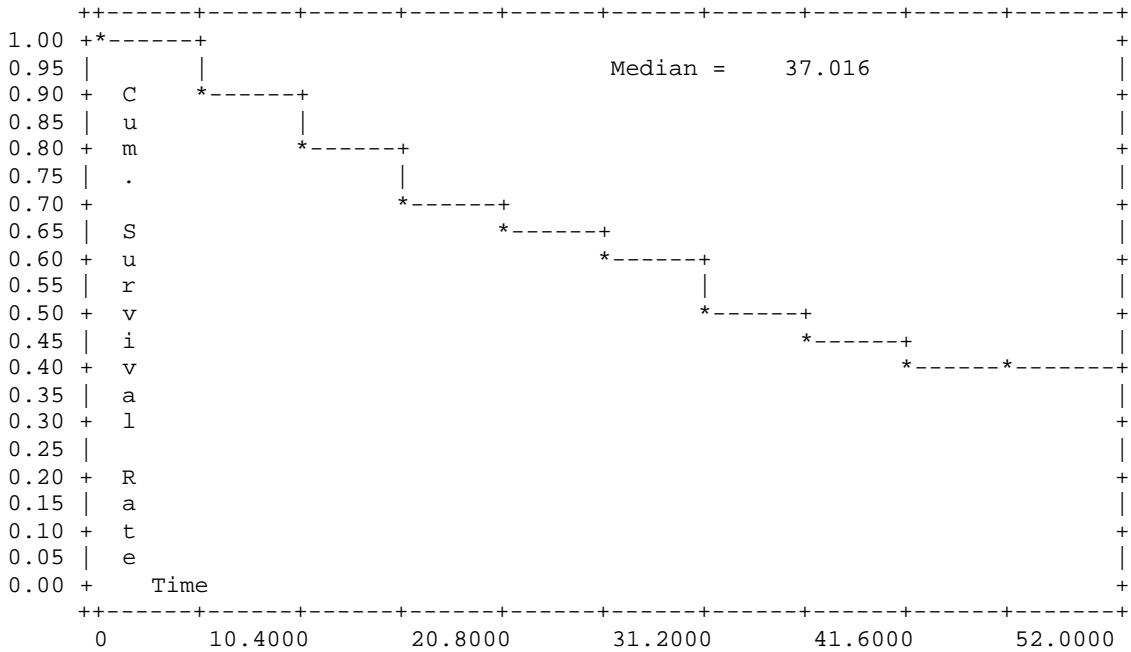
The survival function, hazard function and integrated hazard function in this model specification are graphed below.

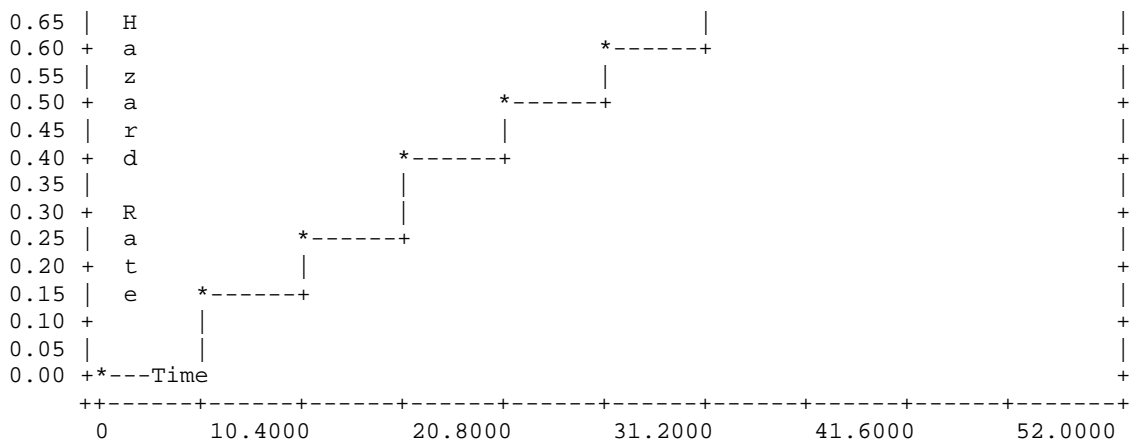
Percentiles of survival distribution:

SURVIVAL	0.25	0.50	0.75	0.95
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TIME 69.28 31.78 11.83 1.70

Parameters of underlying density at data means:





Then we plug in different variables and run the regression, and we found the most controversial thing among all the estimates is university education, that is, in some regressions, we found a positive relationship between unemployment duration with university degree but in a few we found it is negative. So we guess it is not appropriate to put university education as a key independent variable in duration model. Intuitively, when people get university educated, they tend to prefer positions with higher wage rate to compensate their human capital investment and/or tend to find a job that satisfies them or fit their capacities better while those only have high school education would like accept job offers with various wage rate since they have less special professional expertise, in this sense, university degree could prolong the unemployment duration for university educated people (likewise in the job search model, they can be seen as those who have higher reservation wages), however on the other hand, when the economy booms up, the structure of the job vacancies in the economy will be changed and a common view is that more positions for university educated people will be offered in a developed economy. Therefore, the effect of university degree on unemployment duration is ambiguous and our empirical study supports this.

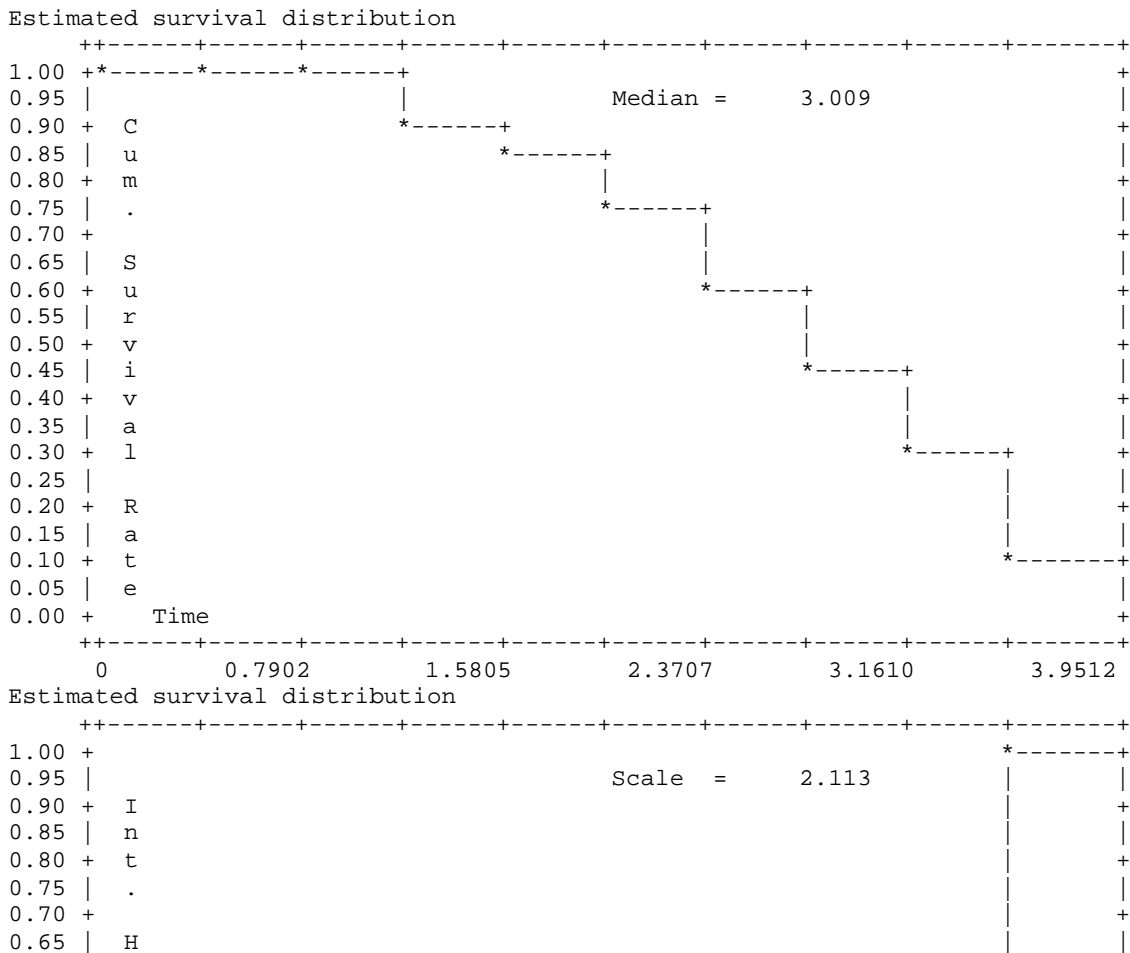
Finally, we run the regression in semi-parametric specification, i.e., Cox's proportional hazard model. The following list lists the estimated coefficients and their test statistics.

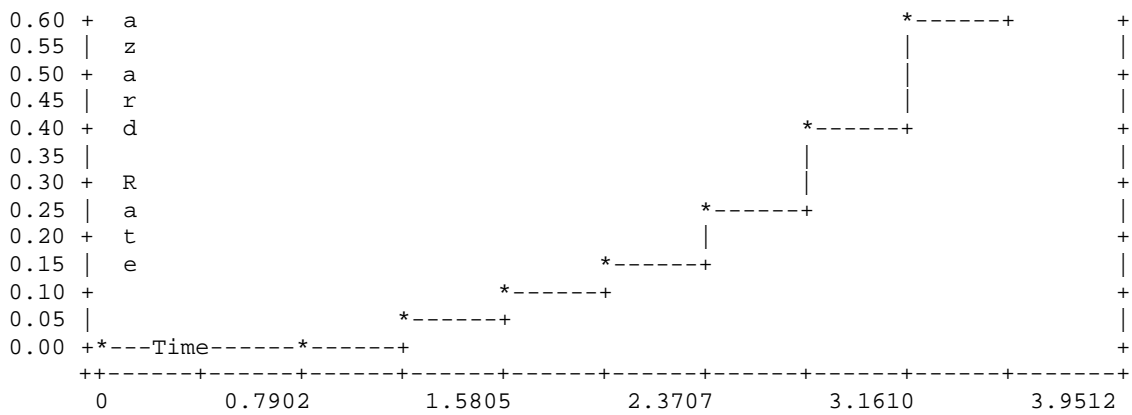
As we can see, with the change of model specification, we found that the signs of some estimates changed.

Variable	Coefficient	Std. Error	t-ratio	Prob.	Mean & S.D. of Var.
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E2	-0.35875E-01	0.1488	-0.241	0.8095	0.1531	0.3605
E3	0.48356E-01	0.1676	0.288	0.7730	0.1137	0.3178
E4	0.21099	0.3826	0.552	0.5813	0.0186	0.1351
E5	0.93432E-01	0.1363	0.685	0.4931	0.1763	0.3815
SEX	0.80598E-01	0.1154	0.698	0.4850	0.6125	0.4877
KID	-0.16247	0.9434E-01	-1.722	0.0851	0.2552	0.5905
INDUS	-0.97063E-02	0.3854E-02	-2.518	0.0118	31.6937	13.7279
OCCUP	0.11775E-01	0.4819E-02	2.444	0.0145	31.0116	12.3287
A2	0.59549E-01	0.3114	0.191	0.8483	0.1903	0.3930
A3	0.79416E-01	0.3096	0.257	0.7975	0.2993	0.4585
A4	0.28112E-01	0.3082	0.091	0.9273	0.2668	0.4428
A5	0.80944E-01	0.3188	0.254	0.7996	0.1508	0.3583
A6	-0.16814	0.3502	-0.480	0.6311	0.0650	0.2468
JSPELL	-0.42145E-03	0.3830E-03	-1.100	0.2712	71.9582	160.7391

The estimated survival function and integrated hazard function for this proportional hazard model are graphed below.





To well understand and follow the estimation, we coded the progem in TSP. In the attached TSP programs, we use the values of the coefficients estimated by ordinary least square as the starting values and then apply miximum log-likelihood procedure.

We used a constant, gender, marital status, educational level, wage rate of previous job, number of children and search effort as independent variables. The estimated coefficients and test statistics are listed below. The model is Weibull without heterogeneity.

Parameter	Estimate	Error	t-statistic
B0	6.58415	.262969	25.0378
B1	-.163541	.100910	-1.62066
B2	-.147650	.094346	-1.56499
B3	-.187067	.108536	-1.72356
B4	-.107628	.112319	-.958232
B5	.111018	.212886	.521490
B6	-.021689	.133226	-.162795
B7	-.497548E-02	.801928E-02	-.620440
B8	.087193	.075925	1.14840
B9	-4.01130	.228722	-17.5379
P	.997343	.040643	24.5389

	P	LAMBDA	MEDIAN
Value	0.99734	0.061554	11.26078

This estimate suggests that married people go to new job more quicker; men are more easier to get a new job in the labor market; university educated people suffer longer unemployment duration than others however test statistics show it is not significant; wage

rate of previous job seems do not matter to the time to find a new job; more kids keep people have longer unemployment duration, and, most significantly, the more effort one pays in job hunting, the more short time one will suffer on unemployment duration.

Another TSP program allows heterogeneity and the estimates and test statistics are list here.

Parameter	Estimate	Error	t-statistic
B0	6.60497	.324871	20.3311
B1	-.160905	.100658	-1.59853
B2	-.145597	.094479	-1.54104
B3	-.181731	.111183	-1.63453
B4	-.102464	.113576	-.902164
B5	.110878	.212011	.522983
B6	-.021806	.132697	-.164325
B7	-.478711E-02	.811660E-02	-.589792
B8	.085208	.075630	1.12665
B9	-4.02569	.280847	-14.3341
THETA	-.017151	.117873	-.145503
P	.988574	.076815	12.8695

The estimates do not change a lot after introduced heterogeneity. And the t -statistic for q shows the estimate of it is not significant. The graphs of estimated hazard function, survival function and integrated hazard function are plotted here below.

ML procedure in TSP maximizes the function with respect to the parameters using a standard gradient method. It uses analytic first and second derivatives.

	P	LAMBDA	MEDIAN
Value	0.98857	0.060051	11.54272

PLOT OF HAZARD VERSUS T

9. References:

1. Anderson, Patricia and Meyer, Bruce (1997), Unemployment Insurance Take-up Rates and the After Tax Value of Benefits. *Quarterly Journal of Economics*.
2. Belzil, Christian (1994), Unemployment Insurance and Unemployment Over Time: An Analysis With Event History Data, *Review of Economics and Statistics*,
3. Kiefer, Nicholas(1988), Economic Duration Data and Hazard Function, *Journal of Economic Literature*,
4. Meyer, Bruce(1990), Unemployment Insurance and Unemployment Spells, *Econometrica*

Appendix 1.

TSP Version 4.3A
(05/17/95) AXP/OpenVMS 4MB
Copyright (C) 1995 TSP International
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06/26/98 1:12 PM

In case of questions or problems, see your local TSP
consultant or send a description of the problem and the
associated TSP output to:

TSP International
P.O. Box 61015, Station A
Palo Alto, CA 94306
USA

```
PROGRAM
LINE *****
1 options crt;
2 supres smpl;
3 load (file='lmas90.txt')
  age1,age2,age3,age4,age5,age6,sex,married,edu1,edu2,
3
  edu3,edu4,edu5,kid,uibw,jspell,wage1,search,d,uspell,
3
  wage2,indust,occup;
4 set nob=@nob;
5 t = uspell;
6 smpl 1,nobs;
7 smplif uspell>0;
8 lt=log(t);
9
9 ? The starting values are the OLS estimates
9
9 supres @logl,@coef;
10 olsq(silent) lt c,sex, married, edu2,edu3,edu4,edu5,wage1,kid,search;
11 mat beta=@coef;
12 set sigma=@S;
13 set p=1/sigma;
14 title 'Starting Values';
15 print beta,p;
16
16 ? Maximum-Likelihood Estimation
16
16 frml loglike logl = d*log(h) + log(S);
17 frml hazard1 h = lambda*p*(lambda*t)**(p-1);
18 frml surviv S = exp[-(lambda*t)**p];
19 frml lambdai lambda = exp[-(XB)];
20 frml NLXB XB = B0 + B1*sex+ B2*married + B3*edu2 + B4*edu3 +
  B5*edu4+
20 B6*edu5 + B7*wage1 +B8*kid +B9*search;
21 param B0 2.78 B1 -.145 B2 -.045 B3 -.0068 B4 .0179 B9 -.904 B5 .269
21 B6 .112 B7 -.006 B8 .104 p .98;
22 eqsub lambdai NLXB;
23 eqsub surviv lambdai;
24 eqsub hazard1 lambdai;
25 eqsub loglike surviv;
26 eqsub loglike hazard1;
27 nosupres @logl,@coef;
28 ml(maxit=50) loglike;
29
29 set sum=0;
30 do i=1 to nob;
31 if t(i)>0; then; set sum=sum+t(i);
34 enddo;
35 set tbar=sum/@nob; ? note: @nob refers to the reduced smpl
  here
36 set lambda=tbar**(-1/p);
37 set Median=log(2)/lambda;
38 print p,lambda,Median;
39
39 smpl 1,nobs;
40 hazard=(lambda**p)*p*(t**(p-1));
```

```

41 survivor=exp(-(lambda*t)**p);
42 inhazard=-log(survivor);
43 graph hazard,t;
44 graph survivor,t;
45 graph inhazard,t;
46 end;

```

EXECUTION

Starting Values

=====

BETA

```

1
1      2.77942
2     -0.14465
3     -0.045413
4     -0.067975
5      0.017925
6      0.26947
7      0.11203
8     -0.0058002
9      0.10418
10     -0.90416

```

P = 0.98029

MAXIMUM LIKELIHOOD ESTIMATION

=====

EQUATION: LOGLIKE

Working space used: 37997

STARTING VALUES

	B0	B1	B2	B3	B4
VALUE	2.78000	-0.14500	-0.045000	-0.0068000	0.017900

	B5	B6	B7	B8	B9
VALUE	0.26900	0.11200	-0.0060000	0.10400	-0.90400

	P
VALUE	0.98000

F=	3659.4	FNEW=	2685.5	ISQZ=	2	STEP=	2.0000	CRIT=	896.82
F=	2685.5	FNEW=	2325.2	ISQZ=	2	STEP=	2.0000	CRIT=	495.18
F=	2325.2	FNEW=	2323.4	ISQZ=	1	STEP=	1.0000	CRIT=	34.317
F=	2323.4	FNEW=	2315.2	ISQZ=	1	STEP=	1.0000	CRIT=	22.369
F=	2315.2	FNEW=	2314.4	ISQZ=	1	STEP=	1.0000	CRIT=	5.4443
F=	2314.4	FNEW=	2314.1	ISQZ=	1	STEP=	1.0000	CRIT=	3.6125
F=	2314.1	FNEW=	2313.4	ISQZ=	1	STEP=	0.50000	CRIT=	2.8508
F=	2313.4	FNEW=	2313.4	ISQZ=	1	STEP=	1.0000	CRIT=	0.27351E-01
F=	2313.4	FNEW=	2313.4	ISQZ=	1	STEP=	0.50000	CRIT=	0.17774E-01
F=	2313.4	FNEW=	2313.4	ISQZ=	1	STEP=	1.0000	CRIT=	0.54350E-04
F=	2313.4	FNEW=	2313.4	ISQZ=	1	STEP=	1.0000	CRIT=	0.64742E-05
F=	2313.4	FNEW=	2313.4	ISQZ=	1	STEP=	1.0000	CRIT=	0.23021E-05
F=	2313.4	FNEW=	2313.4	ISQZ=	1	STEP=	1.0000	CRIT=	0.18631E-05

CONVERGENCE ACHIEVED AFTER 13 ITERATIONS

50 FUNCTION EVALUATIONS.

LOG OF LIKELIHOOD FUNCTION = -2313.44

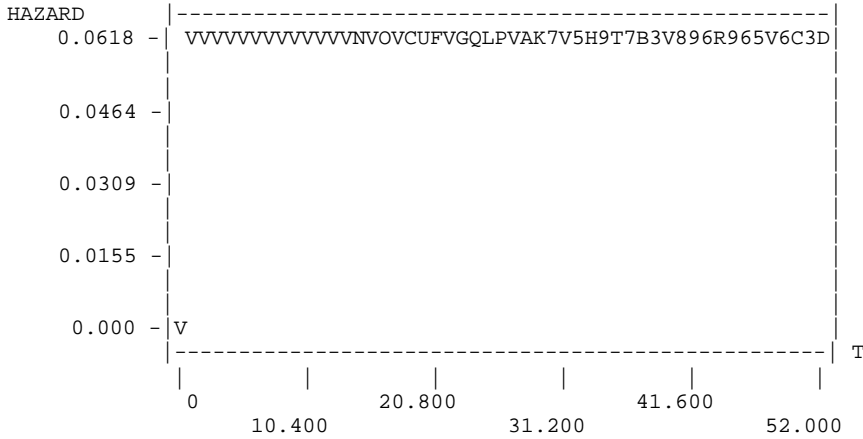
NUMBER OF OBSERVATIONS = 1651

Parameter	Estimate	Standard Error	t-statistic
B0	6.58415	.262969	25.0378
B1	-.163541	.100910	-1.62066
B2	-.147650	.094346	-1.56499
B3	-.187067	.108536	-1.72356
B4	-.107628	.112319	-.958232
B5	.111018	.212886	.521490
B6	-.021689	.133226	-.162795
B7	-.497548E-02	.801928E-02	-.620440
B8	.087193	.075925	1.14840
B9	-4.01130	.228722	-17.5379
P	.997343	.040643	24.5389

Standard Errors computed from covariance of analytic first derivatives (BHHH)

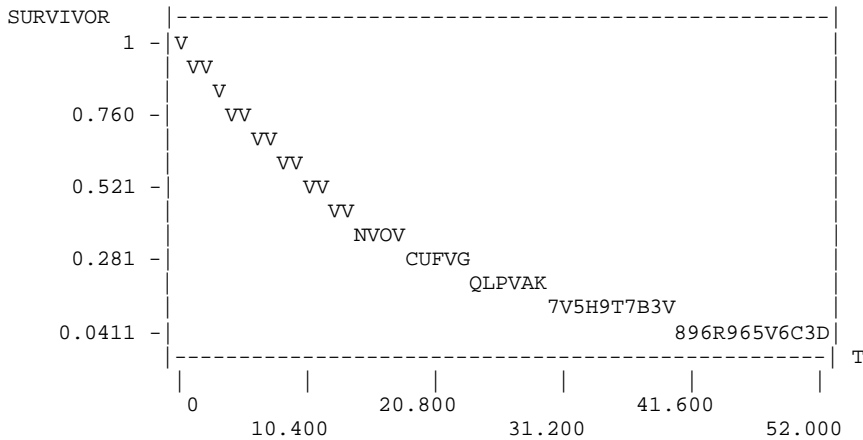
Value	P	LAMBDA	MEDIAN
	0.99734	0.061554	11.26078

PLOT OF HAZARD VERSUS T
=====



TIES [10-30] PRINTED AS [A-U]
[31- 378]: V

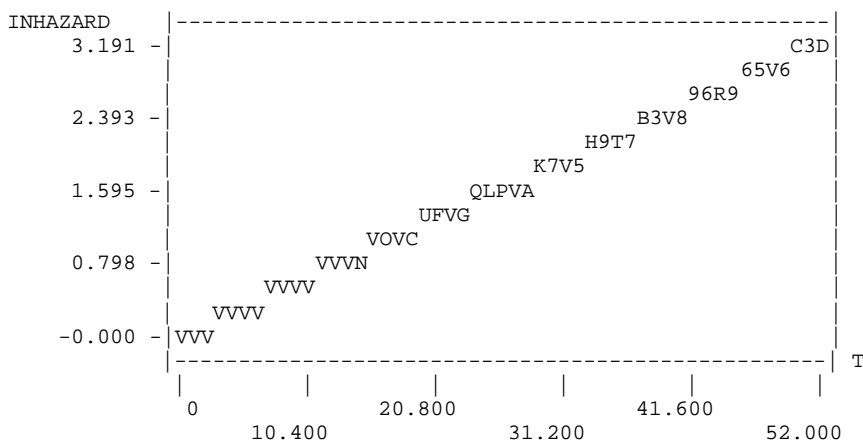
PLOT OF SURVIVOR VERSUS T
=====



TIES [10-30] PRINTED AS [A-U]

[31- 378]: V

PLOT OF INHAZARD VERSUS T
=====



TIES [10-30] PRINTED AS [A-U]
[31- 378]: V

END OF OUTPUT.

MEMORY USAGE:	ITEM:	DATA ARRAY	TOTAL MEMORY
	UNITS:	(4-BYTE WORDS)	(MEGABYTES)
MEMORY ALLOCATED	:	500000	4.0
MEMORY ACTUALLY REQUIRED	:	141722	2.7
CURRENT VARIABLE STORAGE	:	66243	

Appendix 2.

TSP Version 4.3A
(05/17/95) AXP/OpenVMS 4MB
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06/26/98 1:32 PM

In case of questions or problems, see your local TSP
consultant or send a description of the problem and the
associated TSP output to:

TSP International
P.O. Box 61015, Station A
Palo Alto, CA 94306
USA

```
PROGRAM
LINE *****
1 options crt;
2 supres smpl;
3 load (file='lmas90.txt')
3 age1,age2,age3,age4,age5,age6,sex,married,edu1,edu2,
3 edu3,edu4,edu5,kid,uibw,jspell,wage1,search,d,uspell,
3 wage2,indust,occup;
4 set nobs=@nob;
5 t = uspell;
6 smpl 1,nobs;
7 smplif uspell>0;
8 lt=log(t);
9
9 ? The starting values are the OLS estimates
9
9 supres @logl,@coef;
10 olsq(silent) lt c,sex, married, edu2,edu3,edu4,edu5,wage1,kid,search;
11 mat beta=@coef;
12 set sigma=@S;
13 set p=1/sigma;
14 title 'Starting Values';
15 set theta=-.01;
16 print beta,p, theta;
17
17 ? Maximum-Likelihood Estimation
17
17 frml loglike logl = d*log(h) + log(S);
18 frml hazard1 h = [lambda*p*(lambda*t)**(p-1)]*(S**theta);
19 frml surviv S = [1+theta*(lambda*t)**p]**(-1/theta);
20 frml lambdai lambda = exp[-(XB)];
21 frml NLXB XB = B0 + B1*sex+ B2*married + B3*edu2 + B4*edu3 +
B5*edu4+
21 B6*edu5 + B7*wage1 +B8*kid +B9*search;
22 param B0 2.78 B1 -.145 B2 -.045 B3 -.0068 B4 .0179 B9 -.904 B5 .269
22 B6 .112 B7 -.006 B8 .104 p .98, theta -.01;
23 eqsub lambdai NLXB;
24 eqsub surviv lambdai;
25 eqsub hazard1 lambdai;
26 eqsub hazard1 surviv;
27 eqsub loglike surviv;
28 eqsub loglike hazard1;
29 nosupres @logl,@coef;
30 ml(maxit=50) loglike;
31
31 set sum=0;
32 do i=1 to nobs;
33 if t(i)>0; then; set sum=sum+t(i);
36 enddo;
37 set tbar=sum/@nob; ? note: @nob refers to the reduced smpl
here
38 set lambda=tbar**(-1/p);
39 set Median=log(2)/lambda;
40 print p,lambda,Median;
41
41 smpl 1,nobs;
```

```

42 hazard=(lambda**p)*p*(t**(p-1));
43 survivor=exp(-(lambda*t)**p);
44 inhazard=-log(survivor);
45 graph hazard,t;
46 graph survivor,t;
47 graph inhazard,t;
48 end;

```

EXECUTION

Starting Values
=====

BETA

	1
1	2.77942
2	-0.14465
3	-0.045413
4	-0.067975
5	0.017925
6	0.26947
7	0.11203
8	-0.0058002
9	0.10418
10	-0.90416

P = 0.98029
THETA = -0.0100000

MAXIMUM LIKELIHOOD ESTIMATION
=====

EQUATION: LOGLIKE

Working space used: 38497

STARTING VALUES

	B0	B1	B2	B3	B4
VALUE	2.78000	-0.14500	-0.045000	-0.0068000	0.017900
	B5	B6	B7	B8	B9
VALUE	0.26900	0.11200	-0.0060000	0.10400	-0.90400
	THETA	P			
VALUE	-0.0100000	0.98000			

F=	3681.0	FNEW=	2862.1	ISQZ=	2	STEP=	2.0000	CRIT=	965.21
F=	2862.1	FNEW=	2373.0	ISQZ=	2	STEP=	2.0000	CRIT=	444.41

IN OBSERVATION 21 COMPUTING LOG LIKELIHOOD.

F=	2373.0	FNEW=	2333.3	ISQZ=	1	STEP=	0.50000	CRIT=	114.44
F=	2333.3	FNEW=	2317.1	ISQZ=	1	STEP=	1.0000	CRIT=	40.165
F=	2317.1	FNEW=	2314.1	ISQZ=	1	STEP=	0.50000	CRIT=	12.766
F=	2314.1	FNEW=	2313.5	ISQZ=	1	STEP=	1.0000	CRIT=	1.2997
F=	2313.5	FNEW=	2313.5	ISQZ=	1	STEP=	1.0000	CRIT=	0.27346
F=	2313.5	FNEW=	2313.4	ISQZ=	1	STEP=	0.50000	CRIT=	0.31925
F=	2313.4	FNEW=	2313.4	ISQZ=	1	STEP=	0.50000	CRIT=	0.14397E-01
F=	2313.4	FNEW=	2313.4	ISQZ=	1	STEP=	1.0000	CRIT=	0.20160E-02
F=	2313.4	FNEW=	2313.4	ISQZ=	1	STEP=	0.50000	CRIT=	0.17299E-02
F=	2313.4	FNEW=	2313.4	ISQZ=	1	STEP=	1.0000	CRIT=	0.18623E-03
F=	2313.4	FNEW=	2313.4	ISQZ=	1	STEP=	0.50000	CRIT=	0.23522E-03
F=	2313.4	FNEW=	2313.4	ISQZ=	1	STEP=	1.0000	CRIT=	0.20789E-04

```

F= 2313.4      FNEW= 2313.4      ISQZ= 1 STEP= 0.50000      CRIT= 0.33270E-04
F= 2313.4      FNEW= 2313.4      ISQZ= 1 STEP= 0.50000      CRIT= 0.25720E-05
F= 2313.4      FNEW= 2313.4      ISQZ= 1 STEP= 1.00000      CRIT= 0.37658E-06
F= 2313.4      FNEW= 2313.4      ISQZ= 1 STEP= 0.50000      CRIT= 0.34240E-06
F= 2313.4      FNEW= 2313.4      ISQZ= 1 STEP= 1.00000      CRIT= 0.38011E-07

```

CONVERGENCE ACHIEVED AFTER 19 ITERATIONS

67 FUNCTION EVALUATIONS.

```

LOG OF LIKELIHOOD FUNCTION = -2313.42
NUMBER OF OBSERVATIONS = 1651

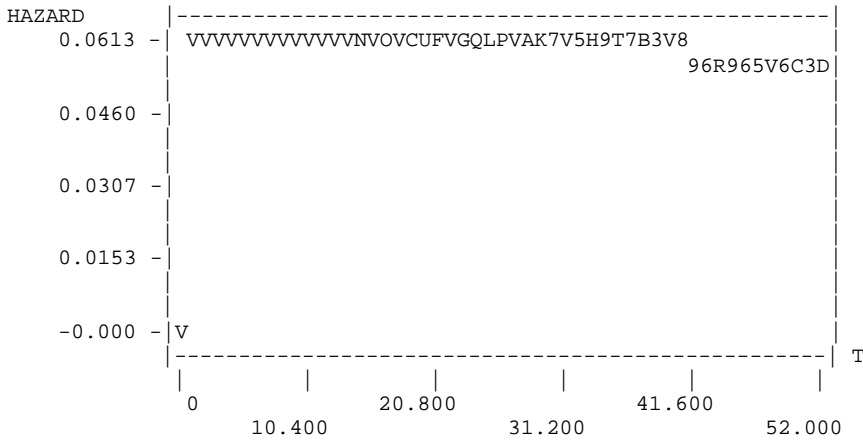
```

Parameter	Estimate	Standard Error	t-statistic
B0	6.60497	.324871	20.3311
B1	-.160905	.100658	-1.59853
B2	-.145597	.094479	-1.54104
B3	-.181731	.111183	-1.63453
B4	-.102464	.113576	-.902164
B5	.110878	.212011	.522983
B6	-.021806	.132697	-.164325
B7	-.478711E-02	.811660E-02	-.589792
B8	.085208	.075630	1.12665
B9	-4.02569	.280847	-14.3341
THETA	-.017151	.117873	-.145503
P	.988574	.076815	12.8695

Standard Errors computed from covariance of analytic first derivatives (BHHH)

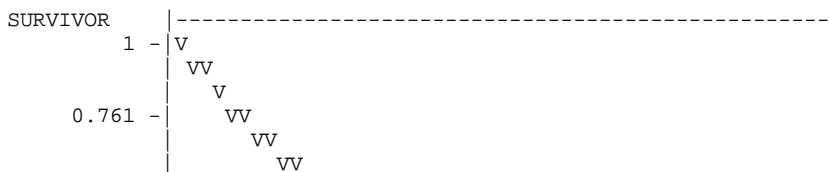
Value	P	LAMBDA	MEDIAN
	0.98857	0.060051	11.54272

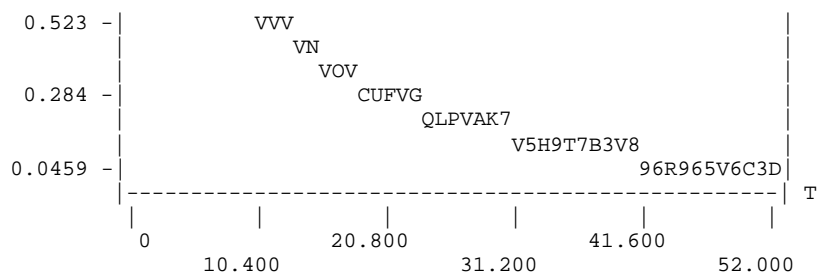
PLOT OF HAZARD VERSUS T
=====



TIES [10-30] PRINTED AS [A-U]
[31- 378]: V

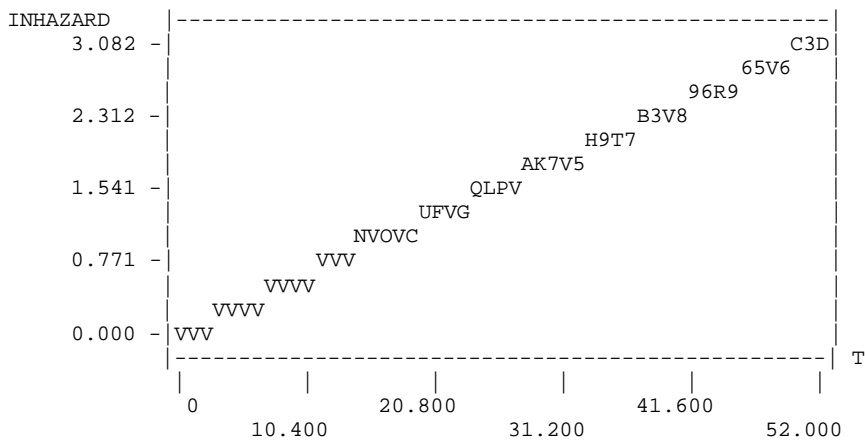
PLOT OF SURVIVOR VERSUS T
=====





TIES [10-30] PRINTED AS [A-U]
 [31- 378]: V

PLOT OF INHAZARD VERSUS T
 =====



TIES [10-30] PRINTED AS [A-U]
 [31- 378]: V

END OF OUTPUT.

MEMORY USAGE:	ITEM:	DATA ARRAY	TOTAL MEMORY
	UNITS:	(4-BYTE WORDS)	(MEGABYTES)
MEMORY ALLOCATED	:	500000	4.0
MEMORY ACTUALLY REQUIRED	:	141814	2.7
CURRENT VARIABLE STORAGE	:	66911	

Appendix 3.

SAMPLE set to observations 1 to 500
 There are 23 variables in the data work area.
 Use STATUS for a list.

1

MODEL COMMAND: SURV; LHS=LT,DI; RHS=ONE,E2,E3,E4,E5,MARI,SEARCH; MODEL=WEIBULL\$

Log-linear survival regression model: WEIBULL
 Least squares is used to obtain starting values for MLE.
 Censoring status variable is DI

Ordinary least squares regression.	Dep. Variable	=	LT
Observations = 431	Weights	=	ONE
Mean of LHS = 0.2336632D+01	Std.Dev of LHS	=	0.1095408D+01
StdDev of residuals= 0.1029026D+01	Sum of squares	=	0.4489709D+03
R-squared = 0.1298417D+00	Adjusted R-squared=	=	0.1175281D+00
F[6, 424] = 0.1054461D+02	Prob value	=	0.6408147D-10
Log-likelihood = -0.6203657D+03	Restr.(b=0) Log-1	=	-0.6503374D+03

N(0,1) used for significance levels.

Variable	Coefficient	Std. Error	t-ratio	Prob.	Mean & S.D. of Var.	
Constant	2.6011	0.1004	25.907	0.0000		
E2	0.17189E-01	0.1438	0.120	0.9048	0.1531	0.3605
E3	-0.46639E-01	0.1620	-0.288	0.7735	0.1137	0.3178
E4	0.20893	0.3751	0.557	0.5775	0.0186	0.1351
E5	-0.28596E-01	0.1367	-0.209	0.8343	0.1763	0.3815
MARI	0.17698E-01	0.1046	0.169	0.8656	0.6381	0.4811
SEARCH	-0.84931	0.1074	-7.908	0.0000	0.3202	0.4671

 Minimization method = D/F/P
 Maximum iterations = 50
 Convergence criteria Gradient = 0.10000E-03
 Function = 0.10000E-03
 Parameters = 0.10000E-04

Starting values: -2.601 -0.1719E-01 0.4664E-01 -0.2089 0.2860E-01
 -0.1770E-01 0.8493 1.029

==> Steepest descent iterations

** Function has converged.

Log-linear survival regression model: WEIBULL

Maximum Likelihood Estimates

Log-Likelihood..... -232.17

N(0,1) used for significance levels.

Variable	Coefficient	Std. Error	t-ratio	Prob.	Mean & S.D. of Var.	
Constant	7.5016	0.6700	11.196	0.0000		
E2	-0.59833E-01	0.2332	-0.257	0.7975	0.1531	0.3605
E3	-0.92575	0.3231	-2.865	0.0042	0.1137	0.3178
E4	0.14208E-01	0.4006	0.035	0.9717	0.0186	0.1351
E5	-0.51936	0.2224	-2.335	0.0195	0.1763	0.3815
MARI	-0.28753	0.1887	-1.524	0.1275	0.6381	0.4811
SEARCH	-4.8325	0.6343	-7.618	0.0000	0.3202	0.4671
Sigma	0.93557	0.8316E-01	11.250	0.0000		

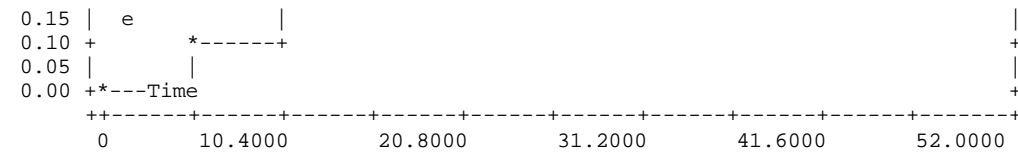
Parameters of underlying density at data means:

(Lambda=exp(bx), P=1/sigma, Median=1/Lambda for Normal and
 Logit,((log2)^1/P)/L for W/E,Boxcox(2,theta)^1/P / L if het)

Parameter	Estimate	Std. Error	Confidence Interval	
Lambda	0.00383	0.00161	0.0007 to	0.0070
P	1.06887	0.09501	0.8827 to	1.2551
Median	185.35192	78.00074	32.4705 to	338.2334

Percentiles of survival distribution:

SURVIVAL	0.25	0.50	0.75	0.95
----------	------	------	------	------



1

MODEL COMMAND: SURV; LHS=LT,DI; RHS=X,SEX,E2,E3,E4,E5,KID,INDUS;HET;MODEL=W
EIBULL\$

Log-linear survival regression model: WEIBULL
Least squares is used to obtain starting values for MLE.
Censoring status variable is DI
WEIBULL MODEL WITH GAMMA HETEROGENEITY

Ordinary least squares regression. Dep. Variable = LT
Observations = 431 Weights = ONE
Mean of LHS = 0.2336632D+01 Std.Dev of LHS = 0.1095408D+01
StdDev of residuals= 0.1081794D+01 Sum of squares = 0.4891766D+03
R-squared = 0.5191826D-01 Adjusted R-squared= 0.2470061D-01
F[12, 418] = 0.1907521D+01 Prob value = 0.3179716D-01
Log-likelihood = -0.6388481D+03 Restr.(b=0) Log-1 = -0.6503374D+03
N(0,1) used for significance levels.

Variable	Coefficient	Std. Error	t-ratio	Prob.	Mean & S.D. of Var.	
Constant	2.1181	0.3561	5.948	0.0000		
A2	-0.19765	0.3352	-0.590	0.5554	0.1903	0.3930
A3	-0.19623	0.3308	-0.593	0.5531	0.2993	0.4585
A4	-0.12725	0.3307	-0.385	0.7004	0.2668	0.4428
A5	-0.22229	0.3410	-0.652	0.5145	0.1508	0.3583
A6	0.20019	0.3753	0.533	0.5937	0.0650	0.2468
SEX	-0.10504	0.1153	-0.911	0.3623	0.6125	0.4877
E2	0.14082E-01	0.1532	0.092	0.9268	0.1531	0.3605
E3	-0.12085	0.1764	-0.685	0.4933	0.1137	0.3178
E4	-0.82584E-01	0.3929	-0.210	0.8335	0.0186	0.1351
E5	-0.12476	0.1473	-0.847	0.3970	0.1763	0.3815
KID	0.20355	0.9415E-01	2.162	0.0306	0.2552	0.5905
INDUS	0.13152E-01	0.4047E-02	3.250	0.0012	31.6937	13.7279

Minimization method = D/F/P
Maximum iterations = 50
Convergence criteria Gradient = 0.10000E-03
Function = 0.10000E-03
Parameters = 0.10000E-04
Starting values: -2.118 0.1976 0.1962 0.1272 0.2223
-0.2002 0.1050 -0.1408E-01 0.1208 0.8258E-01
0.1248 -0.2035 -0.1315E-01 0.1000E-01 1.082
==> Steepest descent iterations

** Function has converged.

Log-linear survival regression model: WEIBULL

Maximum Likelihood Estimates
Log-Likelihood..... -429.57
N(0,1) used for significance levels.

Variable	Coefficient	Std. Error	t-ratio	Prob.	Mean & S.D. of Var.	
Constant	3.7445	0.7367	5.083	0.0000		
A2	0.18543E-01	0.6145	0.030	0.9759	0.1903	0.3930
A3	-0.13404	0.6068	-0.221	0.8252	0.2993	0.4585
A4	0.17546	0.6110	0.287	0.7740	0.2668	0.4428
A5	-0.10144E-01	0.6224	-0.016	0.9870	0.1508	0.3583
A6	0.83122	0.7162	1.161	0.2458	0.0650	0.2468
SEX	-0.62265	0.2206	-2.823	0.0048	0.6125	0.4877
E2	0.28729	0.2891	0.994	0.3204	0.1531	0.3605
E3	0.29863E-01	0.2925	0.102	0.9187	0.1137	0.3178
E4	-0.67356	0.5214	-1.292	0.1964	0.0186	0.1351
E5	-0.26870	0.2276	-1.181	0.2377	0.1763	0.3815
KID	0.37945	0.1776	2.136	0.0326	0.2552	0.5905

```

INDUS      0.11384E-01  0.7001E-02  1.626  0.1039      31.6937  13.7279
Theta     0.58168E-06  0.6274      0.000  1.0000
Sigma     1.1242      0.1841      6.105  0.0000

```

Parameters of underlying density at data means:
(Lambda=exp(bx), P=1/sigma, Median=1/Lambda for Normal and
Logit,((log2)^1/P)/L for W/E,Boxcox(2,theta)^1/P / L if het)

Parameter	Estimate	Std. Error	Confidence Interval
Lambda	0.02084	0.00720	0.0067 to 0.0350
P	0.88955	0.14571	0.6040 to 1.1751
Median	31.78481	10.98547	10.2533 to 53.3163

Percentiles of survival distribution:

```

SURVIVAL    0.25    0.50    0.75    0.95

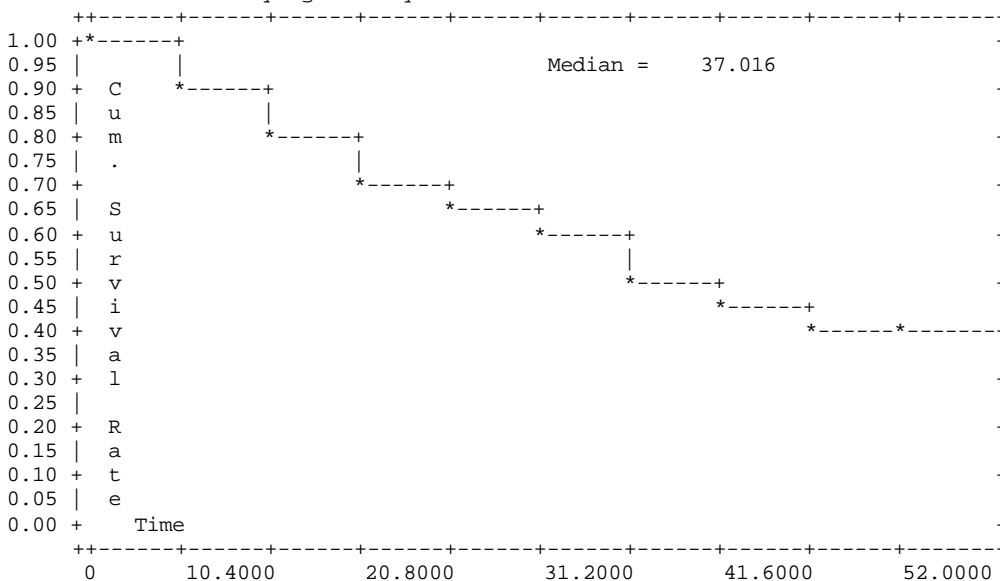
```

```

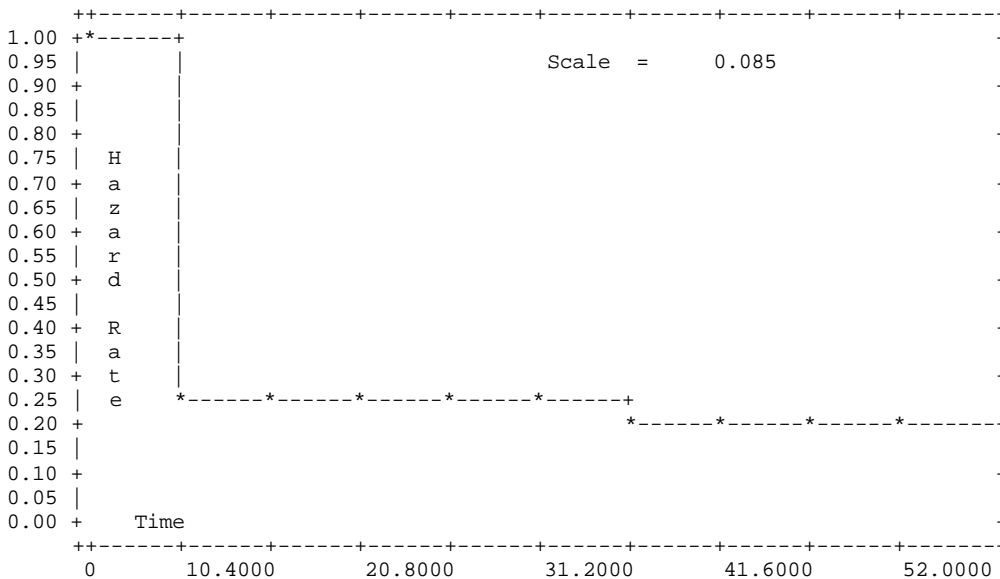
TIME        69.28   31.78   11.83   1.70

```

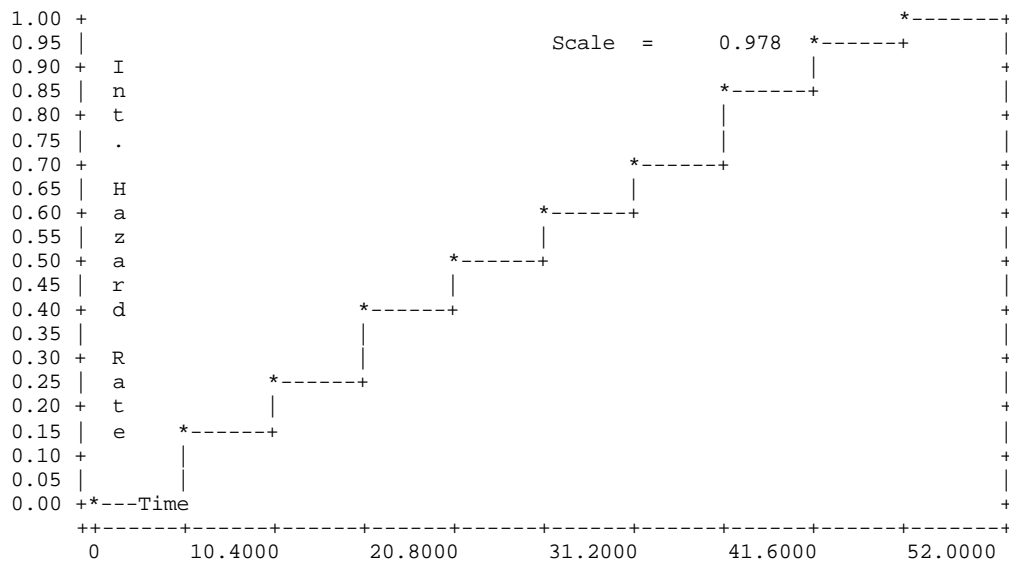
Parameters of underlying density at data means:



Parameters of underlying density at data means:



Parameters of underlying density at data means:



1

MODEL COMMAND: SURV; LHS=LT; RHS=ONE,E2,E3,E4,E5,INDUS,OCCUP;MODEL=WEIBULL\$

Log-linear survival regression model: WEIBULL
 Least squares is used to obtain starting values for MLE.

Ordinary least squares regression. Dep. Variable = LT
 Observations = 431 Weights = ONE
 Mean of LHS = 0.2336632D+01 Std.Dev of LHS = 0.1095408D+01
 StdDev of residuals= 0.1074247D+01 Sum of squares = 0.4892990D+03
 R-squared = 0.5168103D-01 Adjusted R-squared= 0.3826142D-01
 F[6, 424] = 0.3851158D+01 Prob value = 0.9402477D-03
 Log-likelihood = -0.6389021D+03 Restr.(b=0) Log-l = -0.6503374D+03
 N(0,1) used for significance levels.

Variable	Coefficient	Std. Error	t-ratio	Prob.	Mean & S.D. of Var.	
Constant	2.4435	0.2266	10.783	0.0000		
E2	-0.45446E-01	0.1524	-0.298	0.7655	0.1531	0.3605
E3	-0.17174	0.1729	-0.994	0.3205	0.1137	0.3178
E4	-0.31776	0.3903	-0.814	0.4155	0.0186	0.1351
E5	-0.85112E-01	0.1421	-0.599	0.5493	0.1763	0.3815
INDUS	0.11103E-01	0.3968E-02	2.798	0.0051	31.6937	13.7279
OCCUP	-0.13265E-01	0.4512E-02	-2.940	0.0033	31.0116	12.3287

 Minimization method = D/F/P
 Maximum iterations = 50
 Convergence criteria Gradient = 0.10000E-03
 Function = 0.10000E-03
 Parameters = 0.10000E-04
 Starting values: -2.443 0.4545E-01 0.1717 0.3178 0.8511E-01
 -0.1110E-01 0.1326E-01 1.074
 ==> Steepest descent iterations

** Gradient has converged.
 ** Function has converged.

Log-linear survival regression model: WEIBULL

Maximum Likelihood Estimates

Log-Likelihood..... -611.67

N(0,1) used for significance levels.

Variable	Coefficient	Std. Error	t-ratio	Prob.	Mean & S.D. of Var.	
Constant	2.9613	0.2031	14.579	0.0000		
E2	0.47311E-03	0.1364	0.003	0.9972	0.1531	0.3605
E3	-0.48866E-01	0.1465	-0.333	0.7388	0.1137	0.3178

E4	-0.26604	0.3087	-0.862	0.3888	0.0186	0.1351
E5	-0.59146E-01	0.1155	-0.512	0.6085	0.1763	0.3815
INDUS	0.75337E-02	0.3424E-02	2.200	0.0278	31.6937	13.7279
OCCUP	-0.11143E-01	0.4172E-02	-2.671	0.0076	31.0116	12.3287
Sigma	0.84382	0.3995E-01	21.123	0.0000		

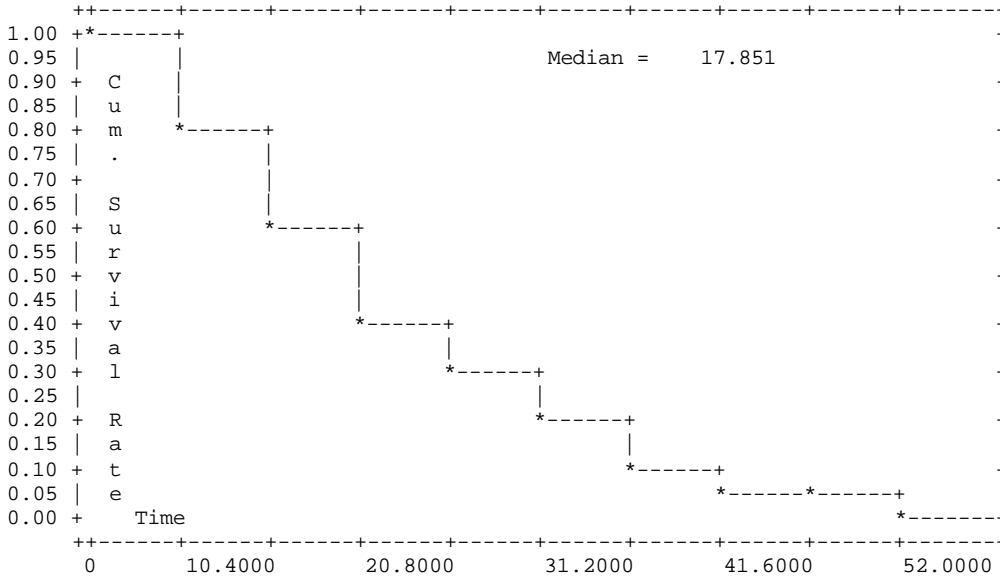
Parameters of underlying density at data means:
(Lambda=exp(bx), P=1/sigma, Median=1/Lambda for Normal and
Logit,((log2)^1/P)/L for W/E,Boxcox(2,theta)^1/P / L if het)

Parameter	Estimate	Std. Error	Confidence Interval
Lambda	0.05880	0.00263	0.0536 to 0.0639
P	1.18509	0.05610	1.0751 to 1.2951
Median	12.48299	0.55782	11.3897 to 13.5763

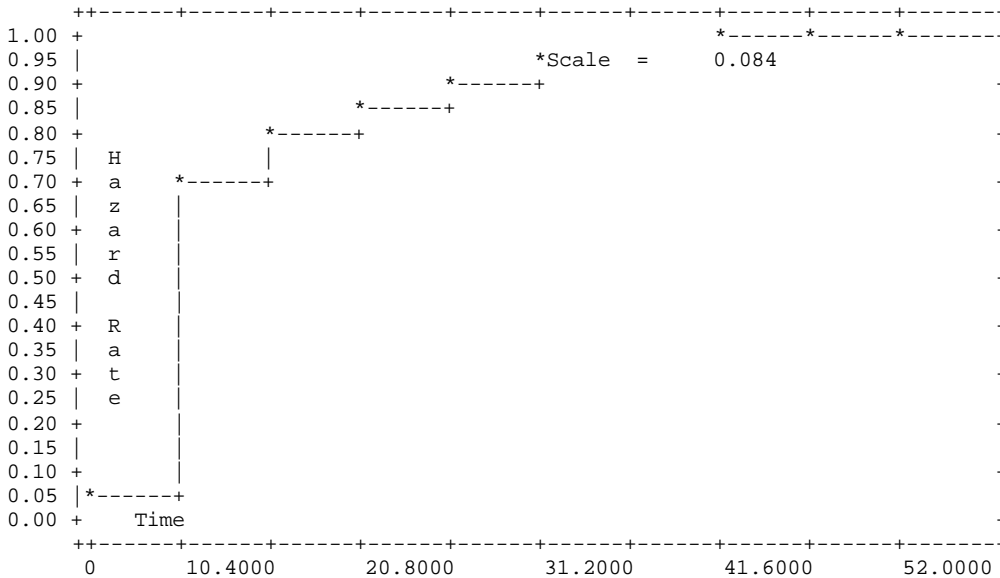
Percentiles of survival distribution:

SURVIVAL	0.25	0.50	0.75	0.95
TIME	22.40	12.48	5.94	1.39

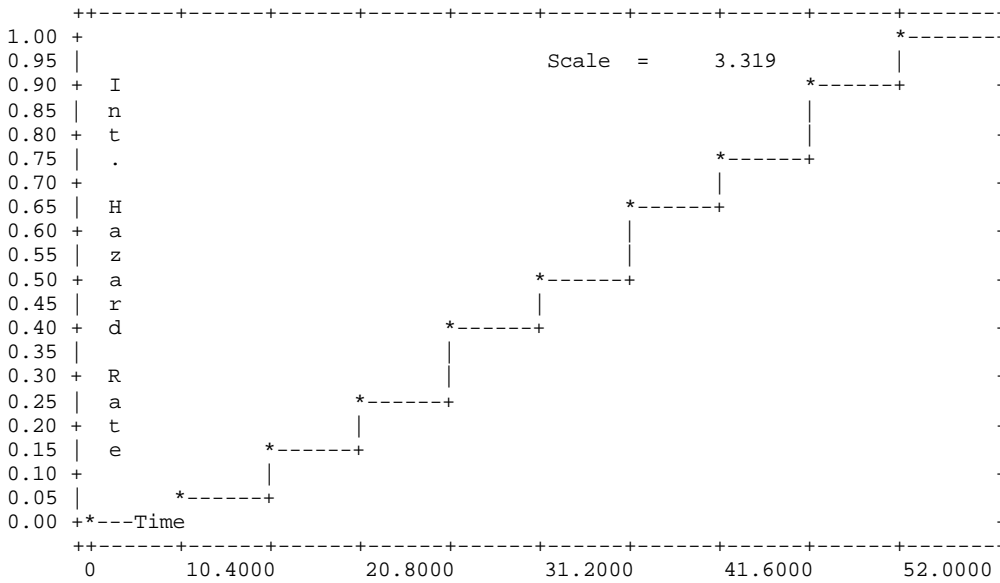
Parameters of underlying density at data means:



Parameters of underlying density at data means:



Parameters of underlying density at data means:



1

MODEL COMMAND: SURV; LHS=LT,DI; RHS=ONE,SEX,E2,E3,E4,E5,KID,INDUS;HET;MODEL
=WEIBULL\$

Log-linear survival regression model: WEIBULL
Least squares is used to obtain starting values for MLE.
Censoring status variable is DI
WEIBULL MODEL WITH GAMMA HETEROGENEITY

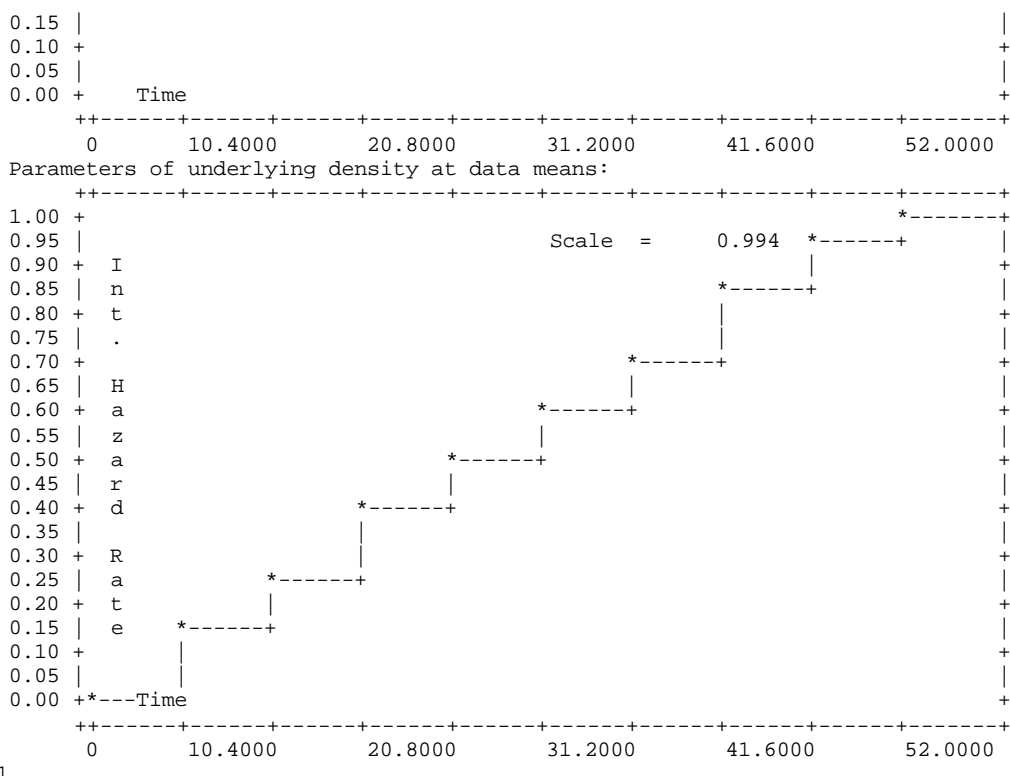
Ordinary least squares regression. Dep. Variable = LT
Observations = 431 Weights = ONE
Mean of LHS = 0.2336632D+01 Std.Dev of LHS = 0.1095408D+01
StdDev of residuals= 0.1080186D+01 Sum of squares = 0.4935567D+03
R-squared = 0.4342901D-01 Adjusted R-squared= 0.2759923D-01
F[7, 423] = 0.2743500D+01 Prob value = 0.8533424D-02
Log-likelihood = -0.6407692D+03 Restr.(b=0) Log-l = -0.6503374D+03
N(0,1) used for significance levels.

Variable	Coefficient	Std. Error	t-ratio	Prob.	Mean & S.D. of Var.
Constant	1.9506	0.1756	11.110	0.0000	
SEX	-0.75781E-01	0.1131	-0.670	0.5030	0.6125 0.4877
E2	-0.38376E-02	0.1518	-0.025	0.9798	0.1531 0.3605
E3	-0.14126	0.1731	-0.816	0.4145	0.1137 0.3178
E4	-0.11592	0.3889	-0.298	0.7656	0.0186 0.1351
E5	-0.12405	0.1452	-0.854	0.3930	0.1763 0.3815
KID	0.18562	0.9028E-01	2.056	0.0398	0.2552 0.5905
INDUS	0.13433E-01	0.4029E-02	3.334	0.0009	31.6937 13.7279

Minimization method = D/F/P
Maximum iterations = 50
Convergence criteria Gradient = 0.10000E-03
Function = 0.10000E-03
Parameters = 0.10000E-04
Starting values: -1.951 0.7578E-01 0.3838E-02 0.1413 0.1159
0.1241 -0.1856 -0.1343E-01 0.1000E-01 1.080
==> Steepest descent iterations

** Function has converged.

Log-linear survival regression model: WEIBULL
Maximum Likelihood Estimates
Log-Likelihood..... -433.30
N(0,1) used for significance levels.
Variable Coefficient Std. Error t-ratio Prob. Mean & S.D. of Var.



1

```

MODEL COMMAND: SURV; LHS=LT; RHS=E2,E3,E4,E5,SEX, KID, INDUS, OCCUP, X,JSPE
                LL$
Cox Proportional Hazard Model
Duration variable is          LT
Status is given by variable  ONE
Total Number of Observations = 431
Total Number of Observations Exiting = 431
Total Number of Observations Censored = 0
Total Number of Distinct Exit Times = 50

*****
Minimization method          =          NEWTON
Maximum iterations           =          25
Convergence criteria         Gradient = 0.10000E-03
                             Function  = 0.10000E-03
                             Parameters = 0.10000E-04

Starting values:  0.0000E+00 0.0000E+00 0.0000E+00 0.0000E+00 0.0000E+00
                  0.0000E+00 0.0000E+00 0.0000E+00 0.0000E+00 0.0000E+00
                  0.0000E+00 0.0000E+00 0.0000E+00 0.0000E+00

==> NEWTON Iterations
Iteration:  1 Fn= 2205.738

** Gradient has converged.
** Function has converged.
** B-vector has converged.
*****

Cox Proportional Hazard Model
Maximum Likelihood Estimates
Log-Likelihood..... -2188.4
Restricted (Slopes=0) Log-L. -2205.7
Chi-Squared (14)..... 34.758
Significance Level..... 0.15962E-02
Log-rank test with 14 degrees of freedom:
Chi-squared = 34.107 - probability = 0.0020
N(0,1) used for significance levels.
Variable Coefficient Std. Error t-ratio Prob. Mean & S.D. of Var.
-----

```

E2	-0.35875E-01	0.1488	-0.241	0.8095	0.1531	0.3605
E3	0.48356E-01	0.1676	0.288	0.7730	0.1137	0.3178
E4	0.21099	0.3826	0.552	0.5813	0.0186	0.1351
E5	0.93432E-01	0.1363	0.685	0.4931	0.1763	0.3815
SEX	0.80598E-01	0.1154	0.698	0.4850	0.6125	0.4877
KID	-0.16247	0.9434E-01	-1.722	0.0851	0.2552	0.5905
INDUS	-0.97063E-02	0.3854E-02	-2.518	0.0118	31.6937	13.7279
OCCUP	0.11775E-01	0.4819E-02	2.444	0.0145	31.0116	12.3287
A2	0.59549E-01	0.3114	0.191	0.8483	0.1903	0.3930
A3	0.79416E-01	0.3096	0.257	0.7975	0.2993	0.4585
A4	0.28112E-01	0.3082	0.091	0.9273	0.2668	0.4428
A5	0.80944E-01	0.3188	0.254	0.7996	0.1508	0.3583
A6	-0.16814	0.3502	-0.480	0.6311	0.0650	0.2468
JSPELL	-0.42145E-03	0.3830E-03	-1.100	0.2712	71.9582	160.7391

Estimated survival distribution
 11th row = t(max) from sample data
 Survival Prob(t ≤ T) Survival Rate

0.0	0.00000	1.00000
0.4	0.03027	0.96973
0.8	0.06659	0.93341
1.2	0.11891	0.88109
1.6	0.18559	0.81441
2.0	0.27574	0.72426
2.4	0.40825	0.59175
2.8	0.55759	0.44241
3.2	0.69842	0.30158
3.6	0.87910	0.12090
4.0	1.00000	0.00000

