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# **Survival Analysis for Primary Biliary Cirrhosis Data by using SAS**

*A Research Project Report Submitted By*

**Mayooran, Thevaraja**

*this project report is submitted in partial fulfilment of the requirement for the  
STAT654 (Statistical Methods for Biostat/Survival Analysis) Course*

**Department of Mathematics and Statistics,  
Minnesota State University, Mankato, USA,  
February 2018<sup>©</sup>**

# Survival Analysis for Primary Biliary Cirrhosis Data by using SAS

Mayooran, Thevaraja

Department of Mathematics and Statistics,  
Minnesota State University, Mankato, USA

Email: [thevaraja.mayooran@mnsu.edu](mailto:thevaraja.mayooran@mnsu.edu)

## Abstract

This research works discussed of the Kaplan-Meier estimator and a real data, the sequential primary biliary cirrhosis collected in Mayo clinic, which holds several time dependent covariates and the observations is measured repeatedly fits for the Cox proportional hazard models because the Cox proportional hazard model is the most popular method for survival analysis. Also, by employing the model fit criterion to figure out a suitable model for the real data and the criterion considered were the Akaike information criterion(AIC) for model validation. We find some factors, which have time to event, are agreed the assumptions of Cox proportional hazard model. So, the Cox PH model is proper to the data and the lifetime of patients would be related strongly to the covariates bilirubin, age, presence of edema, SGOT, presence of hepatomegaly, prothrombin time, platelets, albumin and alkaline.

**Keywords:** *Cox proportional hazard model; Kaplan-Meier estimate; AIC;*

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## **1. Introduction.**

Bile is a fluid formed in human liver that works in the digestive process and will help human remove human blood from red blood, cholesterol and toxins. Biliary cirrhosis is the most commonly the autoimmune disease that is in its cells, in the case of bile ducts. As the water cycle increases, harmful substances can accumulate. This can lead to the liver (this is cirrhosis). Among other things, the sufferer may experience abdominal pain, diarrhea and, finally, the liver. The key to biliary cirrhosis is a major risk for cancer. This illustration uses data from a randomized controlled trial of D-penicillamine (DPCA) for the treatment of primary biliary cirrhosis. A total of  $n=312$  consenting subjects were enrolled and randomized to either active treatment or placebo-control (this group received standard care). Time zero is date of diagnosis and initiation of treatment. Study participants were followed to event of end-stage liver disease or censoring. Thus, these are an example of “right” censored data. Over the approximate 10 years of follow-up, 125 events of death (40%) were seen.

## **2. Literature Review**

Already the several scholars in various locations all over the world have done this statistical analysis related medical data survival analysis. The general idea of survival analysis is to create what are known as survival models or survival curves and fit the cox regression model. A survival model or curve is a way of representing how long a patient with a given disease or condition will survive (Balakrishnan et al 2004). While there are quite a few different methods of doing this, the overall idea is to create a model showing the probability of surviving a certain length of time for each type of treatment. These models are based off of empirical data collected by medical researchers of people who are actually being treated using either the new or the old method (Guo 1991). The most simple versions work based solely on how long each individual survived, but more complicated versions also exist, which can take into account a number of other variables (medical history, pre-existing diseases, lifestyle, ethnicity, age, gender, etc.), which are considered to be important in the medical world (Selvin 2008). In Minnesota, C.W. Woodall (2005) and et al studied survival analysis to a large-scale forest inventory for assessment of tree mortality in Minnesota. David S. Knopman, MD, Department of Neurology, Mayo Clinic, Rochester, studied about investigate the relationship between features and definitions of vascular dementia and survival.

## **3. Data preparation and exploration**

### **3.1 Structure of the data**

The data is from the Mayo Clinic trial in primary biliary cirrhosis (PBC) of the liver conducted between 1974 and 1984. A total of 424 PBC patients, referred to Mayo Clinic during that ten-year interval, met eligibility criteria for the randomized placebo-controlled trial of the drug D-

penicillamine. The first 312 cases on the data set aside and determine randomized and hold full data. This data has many laboratory studies, but only 312 patients, one of them left 140 and the rest left, at least 9: 1 (female and male) as databases. The other 112 cases have not been involved in the trial, but they have agreed to have the same degree of responsibility as to the extent to which they will apply for survival. Sixty of those things depend on shortly after discovery, so this data is in 106 cases and 312 people. The purpose of this study is to determine the effects of D-penicillamine and bilirubin for patients living in Primary Biliary Cirrhosis (PBC). The data record gives to drug addicts, diabetes and enrollment, sex, presence of ascites, fluids, spiders and edema, bilirubin blood, albumin, alkaline phosphatase, serum glutamic-oxaloacetic transaminase (SGOT), cubic platelets, prothrombin periods and the history of the disease, etc.

### **3.2 Data exploration**

Any serious endeavor into data analysis should begin with data exploration, in which the researcher becomes familiar with the distributions and typical values of each variable individually, as well as relationships between pairs or sets of variables. This database is the entry and the first PBC data entry, as well as the text for the search for each person's study. Databases based on the data found in Murtaugh PA are found. Dickson ER. Van Dam GM. Malinchoc Mr. Grambsch PM. Langworthy AL. Gips CH. "The first biliary cirrhosis: The survival policy depends on the visit repeatedly." *Hepatology*. 20 (1.1): 126-34, 1994. The basic PBC databases have only the basic configuration process of the search engineer. This data base contains several laboratory detections, but it is only the first 312. Some databases on this file are different from the original PBC files, for example, data errors and prothrombin times and years that are detected during analytics, at work time surveys and datasets. (These two points are discussed in Fleming and Harrington, 4.6.7). Another important factor is that there are many other factors that affect patients when the data collection is collected. One "character" of the data should speak special. The last vision before loss or liver has much to cost covariates than other data lines. The first treatment of these patients is six months, 1 year, and every year later. In these procedures are the visits to the laboratory for a large battery of test. The "Extra" Visitor, which is usually due to the health status, is likely to have been a major part of the homework. Such unexpected rules can get information, and damage the lost costs "(MCAR or MACs) that are considered in the research. From the first published results on the mark Mayo PBC, however, usually contains five percent of the compounds, namely, age, bilirubin, albumin, prothrombin time, and diarrhea.

## 4. Methodology

### 4.1.1 The Kaplan-Meier estimator of the survival function

The Kaplan Meier survival function estimator is calculated as:

$$\hat{S}_t = \prod_{t_i \leq t} \frac{n_i - d_i}{n_i}$$

where  $n_i$  is the number of subjects at risk and  $d_i$  is the number of subjects who fail, both at time  $t_i$ . Thus, each term in the product is the conditional probability of survival beyond time  $t_i$ , meaning the probability of surviving beyond time  $t_i$ , given the subject has survived up to time  $t_i$ . The survival function estimate of the unconditional probability of survival beyond time  $t$  (the probability of survival beyond time  $t$  from the onset of risk) is then obtained by multiplying together these conditional probabilities up to time  $t$  together.

### 4.1.2 Nelson-Aalen estimator of the cumulative hazard function

The simple relationship with the survival function and hazard function,  $S(t) = e^{-H(t)}$ , the cumulative hazard function can be used to estimate the survival function. The Nelson-Aalen estimator is a non-parametric estimator of the cumulative hazard function and is given by:

$$\hat{H}_t = \sum_{t_i} \frac{d_i}{n_i}$$

where  $d_i$  is the number who failed out of  $n_i$  at risk in interval  $t_i$ . The estimator is calculated, then, by summing the proportion of those at risk who failed in each interval up to time  $t$ .

## 4.2. Comparing survival functions using nonparametric tests

### 4.2.1 Tests of equality of the survival function

In the output we find three Chi-square based tests of the equality of the survival function over strata, which support our suspicion that survival differs between genders. The calculation of the statistic for the nonparametric “Log-Rank” and “Wilcoxon” tests is given by:

$$Q = \frac{[\sum_{i=1}^m w_j (d_{ij} - \hat{e}_{ij})]^2}{\sum_{i=1}^m w_j^2 \hat{v}_{ij}}$$

where  $d_{ij}$  is the observed number of failures in stratum  $i$  at time  $t_j$ ,  $\hat{e}_{ij}$  is the expected number of failures in stratum  $i$  at time  $t_j$ ,  $\hat{v}_{ij}$  is the estimator of the variance of  $d_{ij}$ , and  $w_i$  is the weight of the difference at time  $t_j$  (see Hosmer and Lemeshow(2008) for formulas for  $\hat{e}_{ij}$  and  $\hat{v}_{ij}$ ). In a nutshell, these statistics sum the weighted differences between the observed number of failures and the expected number of failures for each stratum at each timepoint, assuming the same survival function of each stratum. In other words, if all strata have the same survival function, then we expect the same proportion to die in each interval. If these proportions systematically differ among strata across time, then the  $Q$  statistic will be large and the null hypothesis of no difference among strata is more likely to be rejected. The log-rank and Wilcoxon tests in the output table differ in the weights  $w_j$  used. The log-rank or Mantel-Haenzel test uses  $w_j=1$ , so differences at all time intervals are weighted equally. The Wilcoxon test uses  $w_j=n_j$ , so that differences are weighted by the number at risk at time  $t_j$ , thus giving more weight to differences that occur earlier in follow-up time. The “-2Log(LR)” likelihood ratio test is a parametric test assuming exponentially distributed survival times and will not be further discussed in this nonparametric section.

#### 4.2.2 Nonparametric estimation of the hazard function

Standard nonparametric techniques do not typically estimate the hazard function directly. However, we can still get an idea of the hazard rate using a graph of the kernel-smoothed estimate. As the hazard function  $h(t)$  is the derivative of the cumulative hazard function  $H(t)$ , we can roughly estimate the rate of change in  $H(t)$  by taking successive differences in  $\hat{H}(t)$  between adjacent time points,  $\Delta\hat{H}(t) = \hat{H}(t_j) - \hat{H}(t_{j-1})$ . SAS computes differences in the Nelson-Aalen estimate of  $H(t)$ . We generally expect the hazard rate to change smoothly (if it changes) over time, rather than jump around haphazardly. To accomplish this smoothing, the hazard function estimate at any time interval is a weighted average of differences within a window of time that includes many differences, known as the bandwidth. Widening the bandwidth smooths the function by averaging more differences together. However, widening will also mask changes in the hazard function as local changes in the hazard function are drowned out by the larger number of values that are being averaged together.

### 4.3. The Cox proportional hazards regression mode

#### 4.3.1 Estimating the hazard function

Whereas with non-parametric methods we are typically studying the survival function, with regression methods we examine the hazard function,  $h(t)$ . The hazard function for a particular time interval gives the probability that the subject will fail in that interval, given that the subject has not failed up to that point in time. The hazard rate can also be interpreted as the rate at which



failures occur at that point in time, or the rate at which risk is accumulated, an interpretation that coincides with the fact that the hazard rate is the derivative of the cumulative hazard function,  $H(t)$ . In regression models for survival analysis, we attempt to estimate parameters which describe the relationship between our predictors and the hazard rate. We would like to allow parameters, the  $\beta$  s, to take on any value, while still preserving the non-negative nature of the hazard rate. A common way to address both issues is to parameterize the hazard function as:

$$h(t|x) = \exp(\beta_0 + \beta_1 x)$$

In this parameterization,  $h(t|x)$  is constrained to be strictly positive, as the exponential function always evaluates to positive, while  $\beta_0$  and  $\beta_1$  are allowed to take on any value. Notice, however, that  $t$  does not appear in the formula for the hazard function, thus implying that in this parameterization, we do not model the hazard rate's dependence on time. A complete description of the hazard rate's relationship with time would require that the functional form of this relationship be parameterized somehow (for example, one could assume that the hazard rate has an exponential relationship with time). However, in many settings, we are much less interested in modeling the hazard rate's relationship with time and are more interested in its dependence on other variables, such as experimental treatment or age. For such studies, a semi-parametric model, in which we estimate regression parameters as covariate effects but ignore (leave unspecified) the dependence on time, is appropriate.

#### 4.3.2 The Cox proportional hazards model

We can remove the dependence of the hazard rate on time by expressing the hazard rate as a product of  $h_0(t)$ , a baseline hazard rate which describes the hazard rates dependence on time alone, and  $r(x, \beta_x)$ , which describes the hazard rates dependence on the other  $x$

Covariates:  $h(t) = h_0(t)r(x, \beta_x)$

In this parameterization,  $h(t)$  will equal  $h_0(t)$  when  $r(x, \beta_x)=1$ . It is intuitively appealing to let  $r(x, \beta_x)=1$  when all  $x = 0$ , thus making the baseline hazard rate,  $h_0(t)$  equivalent to a regression intercept. Above, we discussed that expressing the hazard rate's dependence on its covariates as an exponential function conveniently allows the regression coefficients to take on any value while still constraining the hazard rate to be positive. The exponential function is also equal to 1 when its argument is equal to 0. We will thus let  $r(x, \beta_x) = \exp(x\beta_x)$ , and the hazard function will be given by:  $h(t) = h_0(t)\exp(x\beta_x)$

This parameterization forms the *Cox proportional hazards model*. It is called the proportional hazards model because the ratio of hazard rates between two groups with fixed covariates will stay constant over time in this model. For example, the hazard rate when time  $t$  when  $x = x_1$  would then be  $h(t|x_1) = h_0(t)\exp(x_1\beta_x)$  and at time  $t$  when  $x = x_2$  would be  $h(t|x_2) = h_0(t)\exp(x_2\beta_x)$ . The covariate effect of  $x$ , then is the ratio between these two hazard rates, or a hazard ratio(HR):

$$HR = \frac{h(t|x_1)}{h(t|x_2)} = \frac{h_0(t)\exp(x_1\beta_x)}{h_0(t)\exp(x_2\beta_x)}$$

Notice that the baseline hazard rate,  $h_0(t)$  is cancelled out, and that the hazard rate does not depend on time  $t$ :

$$HR = \exp(\beta_x(x_2 - x_1))$$

The hazard rate  $HR$  will thus stay constant over time with fixed covariates. Because of this parameterization, covariate effects are multiplicative rather than additive and are expressed as hazard ratios, rather than hazard differences. As we see above, one of the great advantages of the Cox model is that estimating predictor effects does not depend on making assumptions about the form of the baseline hazard function,  $h_0(t)$ , which can be left unspecified. Instead, we need only assume that whatever the baseline hazard function is, covariate effects multiplicatively shift the hazard function and these multiplicative shifts are constant over time. Cox models are typically fitted by maximum likelihood methods, which estimate the regression parameters that maximize the probability of observing the given set of survival times. We can similarly calculate the joint probability of observing each of the  $n$  subject's failure times, or the likelihood of the failure times, as a function of the regression parameters,  $\beta$ , given the subject's covariates values  $x_j$ :

$$L(\beta) = \prod_{i=1}^n \frac{\exp(x_i\beta_x)}{\sum \exp(x_i\beta_x)}$$

where  $R_j$  is the set of subjects still at risk at time  $t_j$ . Maximum likelihood methods attempt to find the  $\beta$  values that maximize this likelihood, that is, the regression parameters that yield the maximum joint probability of observing the set of failure times with the associated set of covariate values. Because this likelihood ignores any assumptions made about the baseline hazard function, it is actually a partial likelihood, not a full likelihood, but the resulting  $\beta$  have the same distributional properties as those derived from the full likelihood. Finally we will Fit a simple Cox regression model for this data and discuss some results.

## 5. Result and Discussions

Survival analysis often begins with examination of the overall survival experience through non-parametric methods, such as Kaplan-Meier (product-limit) and life-table estimators of the survival function. Non-parametric methods are appealing because no assumption of the shape of the

survivor function nor of the hazard function need be made. However, nonparametric methods do not model the hazard rate directly nor do they estimate the magnitude of the effects of covariates. So, in this research we are going to use `proc lifetest` function in SAS, at a minimum `proc lifetest` requires specification of a failure time variable, here `futime`, on the time statement.

#### Product-Limit Survival Estimates

<b>futime</b>	<b>Number at Risk</b>	<b>Observed Events</b>	<b>Survival</b>	<b>Failure</b>	<b>Survival Standard Error</b>	<b>Number Failed</b>	<b>Number Left</b>
<b>0.00</b>	312	0	1.0000	0	0	0	312
<b>41.00</b>	312	1	0.9968	0.00321	0.00320	1	311
<b>51.00</b>	311	1	0.9936	0.00641	0.00452	2	310
<b>71.00</b>	310	1	0.9904	0.00962	0.00552	3	309
<b>77.00</b>	309	1	0.9872	0.0128	0.00637	4	308
<b>110.00</b>	308	1	0.9840	0.0160	0.00711	5	307
<b>130.00</b>	307	1	0.9808	0.0192	0.00778	6	306
<b>131.00</b>	306	1	0.9776	0.0224	0.00838	7	305
<b>140.00</b>	305	1	0.9744	0.0256	0.00895	8	304
<b>179.00</b>	304	1	0.9712	0.0288	0.00948	9	303
<b>186.00</b>	303	1	0.9679	0.0321	0.00997	10	302
<b>191.00</b>	302	1	0.9647	0.0353	0.0104	11	301
<b>198.00</b>	301	1	0.9615	0.0385	0.0109	12	300
<b>207.00</b>	300	1	0.9583	0.0417	0.0113	13	299
<b>216.00</b>	299	1	0.9551	0.0449	0.0117	14	298
<b>223.00</b>	298	1	0.9519	0.0481	0.0121	15	297
<b>264.00</b>	.	.	.	.	.	16	296
<b>264.00</b>	297	2	0.9455	0.0545	0.0129	17	295
<b>304.00</b>	295	1	0.9423	0.0577	0.0132	18	294
<b>321.00</b>	294	1	0.9391	0.0609	0.0135	19	293
<b>326.00</b>	293	1	0.9359	0.0641	0.0139	20	292
<b>334.00</b>	292	1	0.9327	0.0673	0.0142	21	291
<b>348.00</b>	291	1	0.9295	0.0705	0.0145	22	290
<b>388.00</b>	290	1	0.9263	0.0737	0.0148	23	289

### Product-Limit Survival Estimates

futime		Number at Risk	Observed Events	Survival	Failure	Survival Standard Error	Number Failed	Number Left
400.00		289	1	0.9231	0.0769	0.0151	24	288
460.00		288	1	0.9199	0.0801	0.0154	25	287
515.00		287	1	0.9167	0.0833	0.0156	26	286
533.00	*	286	0	.	.	.	26	285
549.00		285	1	0.9135	0.0865	0.0159	27	284
552.00		284	1	0.9102	0.0898	0.0162	28	283
597.00		283	1	0.9070	0.0930	0.0164	29	282
611.00		282	1	0.9038	0.0962	0.0167	30	281
673.00		281	1	0.9006	0.0994	0.0169	31	280
694.00		280	1	0.8974	0.1026	0.0172	32	279
708.00		279	1	0.8942	0.1058	0.0174	33	278
732.00	*	278	0	.	.	.	33	277
733.00		277	1	0.8909	0.1091	0.0177	34	276
737.00	*	276	0	.	.	.	34	275
750.00		275	1	0.8877	0.1123	0.0179	35	274
762.00		274	1	0.8844	0.1156	0.0181	36	273
769.00		273	1	0.8812	0.1188	0.0183	37	272
786.00		272	1	0.8780	0.1220	0.0186	38	271
788.00	*	271	0	.	.	.	38	270
790.00		270	1	0.8747	0.1253	0.0188	39	269
797.00		269	1	0.8715	0.1285	0.0190	40	268
799.00		268	1	0.8682	0.1318	0.0192	41	267
824.00		267	1	0.8650	0.1350	0.0194	42	266
837.00	*	266	0	.	.	.	42	265
839.00	*	265	0	.	.	.	42	264
850.00		264	1	0.8617	0.1383	0.0196	43	263
853.00		263	1	0.8584	0.1416	0.0198	44	262

### Product-Limit Survival Estimates

<b>futime</b>	<b>Number at Risk</b>	<b>Observed Events</b>	<b>Survival</b>	<b>Failure</b>	<b>Survival Standard Error</b>	<b>Number Failed</b>	<b>Number Left</b>
<b>859.00</b>	262	1	0.8551	0.1449	0.0200	45	261
<b>877.00</b> *	261	0	.	.	.	45	260
<b>890.00</b>	260	1	0.8518	0.1482	0.0202	46	259
<b>901.00</b> *	259	0	.	.	.	46	258
<b>904.00</b>	258	1	0.8485	0.1515	0.0204	47	257
<b>930.00</b>	257	1	0.8452	0.1548	0.0205	48	256
<b>939.00</b> *	256	0	.	.	.	48	255
<b>943.00</b>	255	1	0.8419	0.1581	0.0207	49	254
<b>971.00</b>	254	1	0.8386	0.1614	0.0209	50	253
<b>974.00</b>	253	1	0.8353	0.1647	0.0211	51	252
<b>980.00</b>	252	1	0.8320	0.1680	0.0213	52	251
<b>994.00</b> *	251	0	.	.	.	52	250
<b>999.00</b>	250	1	0.8287	0.1713	0.0214	53	249
<b>1000.00</b>	249	1	0.8253	0.1747	0.0216	54	248
<b>1012.00</b>	248	1	0.8220	0.1780	0.0218	55	247
<b>1030.00</b> *	247	0	.	.	.	55	246
<b>1037.00</b>	246	1	0.8187	0.1813	0.0219	56	245
<b>1067.00</b> *	245	0	.	.	.	56	244
<b>1077.00</b>	244	1	0.8153	0.1847	0.0221	57	243
<b>1080.00</b>	243	1	0.8119	0.1881	0.0223	58	242
<b>1083.00</b>	242	1	0.8086	0.1914	0.0224	59	241
<b>1084.00</b> *	241	0	.	.	.	59	240
<b>1149.00</b> *	240	0	.	.	.	59	239
<b>1152.00</b>	239	1	0.8052	0.1948	0.0226	60	238
<b>1153.00</b> *	238	0	.	.	.	60	237
<b>1165.00</b>	237	1	0.8018	0.1982	0.0227	61	236
<b>1170.00</b>	236	1	0.7984	0.2016	0.0229	62	235

### Product-Limit Survival Estimates

futime	Number at Risk	Observed Events	Survival	Failure	Survival Standard Error	Number Failed	Number Left
<b>1191.00</b>	.	.	.	.	.	63	234
<b>1191.00</b>	235	2	0.7916	0.2084	0.0232	64	233
<b>1212.00</b>	233	1	0.7882	0.2118	0.0234	65	232
<b>1216.00</b> *	.	0	.	.	.	65	231
<b>1216.00</b> *	232	0	.	.	.	65	230
<b>1217.00</b>	230	1	0.7848	0.2152	0.0235	66	229
<b>1230.00</b> *	229	0	.	.	.	66	228
<b>1234.00</b> *	228	0	.	.	.	66	227
<b>1235.00</b>	227	1	0.7813	0.2187	0.0237	67	226
<b>1250.00</b> *	226	0	.	.	.	67	225
<b>1271.00</b> *	225	0	.	.	.	67	224
<b>1293.00</b> *	224	0	.	.	.	67	223
<b>1295.00</b> *	223	0	.	.	.	67	222
<b>1297.00</b>	222	1	0.7778	0.2222	0.0238	68	221
<b>1300.00</b> *	221	0	.	.	.	68	220
<b>1301.00</b> *	220	0	.	.	.	68	219
<b>1302.00</b> *	219	0	.	.	.	68	218
<b>1320.00</b> *	218	0	.	.	.	68	217
<b>1321.00</b> *	217	0	.	.	.	68	216
<b>1329.00</b> *	216	0	.	.	.	68	215
<b>1349.00</b> *	215	0	.	.	.	68	214
<b>1350.00</b>	214	1	0.7742	0.2258	0.0240	69	213
<b>1356.00</b>	213	1	0.7705	0.2295	0.0241	70	212
<b>1360.00</b>	212	1	0.7669	0.2331	0.0243	71	211
<b>1363.00</b> *	.	0	.	.	.	71	210
<b>1363.00</b> *	211	0	.	.	.	71	209
<b>1401.00</b> *	209	0	.	.	.	71	208

### Product-Limit Survival Estimates

<b>futime</b>		<b>Number at Risk</b>	<b>Observed Events</b>	<b>Survival</b>	<b>Failure</b>	<b>Survival Standard Error</b>	<b>Number Failed</b>	<b>Number Left</b>
<b>1408.00</b>	*	208	0	.	.	.	71	207
<b>1412.00</b>	*	207	0	.	.	.	71	206
<b>1413.00</b>		206	1	0.7632	0.2368	0.0245	72	205
<b>1418.00</b>	*	205	0	.	.	.	72	204
<b>1420.00</b>	*	204	0	.	.	.	72	203
<b>1427.00</b>		203	1	0.7594	0.2406	0.0246	73	202
<b>1433.00</b>	*	202	0	.	.	.	73	201
<b>1434.00</b>		201	1	0.7556	0.2444	0.0248	74	200
<b>1434.00</b>	*	.	0	.	.	.	74	199
<b>1435.00</b>	*	199	0	.	.	.	74	198
<b>1444.00</b>		198	1	0.7518	0.2482	0.0250	75	197
<b>1447.00</b>	*	197	0	.	.	.	75	196
<b>1455.00</b>	*	196	0	.	.	.	75	195
<b>1457.00</b>	*	195	0	.	.	.	75	194
<b>1481.00</b>	*	194	0	.	.	.	75	193
<b>1487.00</b>		193	1	0.7479	0.2521	0.0251	76	192
<b>1492.00</b>		192	1	0.7440	0.2560	0.0253	77	191
<b>1504.00</b>	*	191	0	.	.	.	77	190
<b>1525.00</b>	*	190	0	.	.	.	77	189
<b>1536.00</b>		189	1	0.7401	0.2599	0.0255	78	188
<b>1542.00</b>	*	188	0	.	.	.	78	187
<b>1558.00</b>	*	187	0	.	.	.	78	186
<b>1568.00</b>	*	186	0	.	.	.	78	185
<b>1569.00</b>	*	185	0	.	.	.	78	184
<b>1576.00</b>		184	1	0.7361	0.2639	0.0256	79	183
<b>1592.00</b>	*	183	0	.	.	.	79	182
<b>1614.00</b>	*	.	0	.	.	.	79	181

### Product-Limit Survival Estimates

<b>futime</b>		<b>Number at Risk</b>	<b>Observed Events</b>	<b>Survival</b>	<b>Failure</b>	<b>Survival Standard Error</b>	<b>Number Failed</b>	<b>Number Left</b>
<b>1614.00</b>	*	182	0	.	.	.	79	180
<b>1615.00</b>	*	180	0	.	.	.	79	179
<b>1656.00</b>	*	179	0	.	.	.	79	178
<b>1657.00</b>		178	1	0.7319	0.2681	0.0258	80	177
<b>1666.00</b>	*	177	0	.	.	.	80	176
<b>1677.00</b>	*	176	0	.	.	.	80	175
<b>1682.00</b>		175	1	0.7278	0.2722	0.0260	81	174
<b>1690.00</b>	.	.	.	.	.	.	82	173
<b>1690.00</b>		174	2	0.7194	0.2806	0.0264	83	172
<b>1701.00</b>	*	172	0	.	.	.	83	171
<b>1702.00</b>	*	171	0	.	.	.	83	170
<b>1735.00</b>	*	170	0	.	.	.	83	169
<b>1741.00</b>		169	1	0.7151	0.2849	0.0266	84	168
<b>1765.00</b>	*	168	0	.	.	.	84	167
<b>1769.00</b>	*	167	0	.	.	.	84	166
<b>1770.00</b>	*	166	0	.	.	.	84	165
<b>1776.00</b>	*	165	0	.	.	.	84	164
<b>1783.00</b>	*	164	0	.	.	.	84	163
<b>1785.00</b>	*	163	0	.	.	.	84	162
<b>1786.00</b>		162	1	0.7107	0.2893	0.0268	85	161
<b>1790.00</b>	*	161	0	.	.	.	85	160
<b>1810.00</b>	*	160	0	.	.	.	85	159
<b>1827.00</b>		159	1	0.7063	0.2937	0.0270	86	158
<b>1831.00</b>	*	158	0	.	.	.	86	157
<b>1832.00</b>	*	157	0	.	.	.	86	156
<b>1847.00</b>		156	1	0.7017	0.2983	0.0272	87	155
<b>1874.00</b>	*	155	0	.	.	.	87	154



### Product-Limit Survival Estimates

futime		Number at Risk	Observed Events	Survival	Failure	Survival Standard Error	Number Failed	Number Left
1882.00	*	.	0	.	.	.	87	153
1882.00	*	154	0	.	.	.	87	152
1908.00	*	152	0	.	.	.	87	151
1925.00		151	1	0.6971	0.3029	0.0274	88	150
1932.00	*	150	0	.	.	.	88	149
1945.00	*	149	0	.	.	.	88	148
1951.00	*	148	0	.	.	.	88	147
1967.00	*	147	0	.	.	.	88	146
1978.00	*	146	0	.	.	.	88	145
1979.00	*	145	0	.	.	.	88	144
2022.00	*	144	0	.	.	.	88	143
2033.00	*	143	0	.	.	.	88	142
2050.00	*	142	0	.	.	.	88	141
2055.00		141	1	0.6921	0.3079	0.0276	89	140
2081.00		140	1	0.6872	0.3128	0.0279	90	139
2090.00		139	1	0.6823	0.3177	0.0281	91	138
2105.00		138	1	0.6773	0.3227	0.0283	92	137
2106.00	*	137	0	.	.	.	92	136
2157.00	*	136	0	.	.	.	92	135
2168.00	*	135	0	.	.	.	92	134
2170.00	*	134	0	.	.	.	92	133
2171.00	*	133	0	.	.	.	92	132
2176.00	*	132	0	.	.	.	92	131
2178.00	*	131	0	.	.	.	92	130
2195.00	*	130	0	.	.	.	92	129
2216.00	*	129	0	.	.	.	92	128
2221.00	*	128	0	.	.	.	92	127

### Product-Limit Survival Estimates

<b>futime</b>	<b>Number at Risk</b>	<b>Observed Events</b>	<b>Survival</b>	<b>Failure</b>	<b>Survival Standard Error</b>	<b>Number Failed</b>	<b>Number Left</b>
<b>2224.00</b>	127	1	0.6720	0.3280	0.0286	93	126
<b>2224.00</b> *	.	0	.	.	.	93	125
<b>2241.00</b> *	125	0	.	.	.	93	124
<b>2255.00</b> *	124	0	.	.	.	93	123
<b>2256.00</b>	123	1	0.6665	0.3335	0.0289	94	122
<b>2272.00</b> *	122	0	.	.	.	94	121
<b>2288.00</b>	121	1	0.6610	0.3390	0.0292	95	120
<b>2294.00</b> *	120	0	.	.	.	95	119
<b>2297.00</b>	119	1	0.6554	0.3446	0.0295	96	118
<b>2301.00</b> *	118	0	.	.	.	96	117
<b>2318.00</b> *	117	0	.	.	.	96	116
<b>2330.00</b> *	116	0	.	.	.	96	115
<b>2332.00</b> *	115	0	.	.	.	96	114
<b>2350.00</b> *	114	0	.	.	.	96	113
<b>2357.00</b> *	113	0	.	.	.	96	112
<b>2363.00</b> *	112	0	.	.	.	96	111
<b>2365.00</b> *	111	0	.	.	.	96	110
<b>2386.00</b>	110	1	0.6495	0.3505	0.0298	97	109
<b>2400.00</b>	109	1	0.6435	0.3565	0.0301	98	108
<b>2419.00</b>	108	1	0.6376	0.3624	0.0304	99	107
<b>2443.00</b> *	107	0	.	.	.	99	106
<b>2449.00</b> *	106	0	.	.	.	99	105
<b>2452.00</b> *	105	0	.	.	.	99	104
<b>2456.00</b> *	104	0	.	.	.	99	103
<b>2466.00</b>	103	1	0.6314	0.3686	0.0307	100	102
<b>2468.00</b> *	102	0	.	.	.	100	101
<b>2475.00</b> *	101	0	.	.	.	100	100

### Product-Limit Survival Estimates

<b>futime</b>	<b>Number at Risk</b>	<b>Observed Events</b>	<b>Survival</b>	<b>Failure</b>	<b>Survival Standard Error</b>	<b>Number Failed</b>	<b>Number Left</b>
<b>2503.00</b>	100	1	0.6251	0.3749	0.0311	101	99
<b>2504.00</b>	* .	0	.	.	.	101	98
<b>2504.00</b>	* 99	0	.	.	.	101	97
<b>2527.00</b>	* 97	0	.	.	.	101	96
<b>2540.00</b>	96	1	0.6186	0.3814	0.0314	102	95
<b>2555.00</b>	* 95	0	.	.	.	102	94
<b>2556.00</b>	* 94	0	.	.	.	102	93
<b>2563.00</b>	* 93	0	.	.	.	102	92
<b>2573.00</b>	* 92	0	.	.	.	102	91
<b>2574.00</b>	* 91	0	.	.	.	102	90
<b>2576.00</b>	* 90	0	.	.	.	102	89
<b>2580.00</b>	* 89	0	.	.	.	102	88
<b>2583.00</b>	88	1	0.6115	0.3885	0.0318	103	87
<b>2598.00</b>	87	1	0.6045	0.3955	0.0322	104	86
<b>2609.00</b>	* 86	0	.	.	.	104	85
<b>2615.00</b>	* 85	0	.	.	.	104	84
<b>2624.00</b>	* 84	0	.	.	.	104	83
<b>2644.00</b>	* 83	0	.	.	.	104	82
<b>2657.00</b>	* 82	0	.	.	.	104	81
<b>2666.00</b>	* 81	0	.	.	.	104	80
<b>2689.00</b>	80	1	0.5969	0.4031	0.0327	105	79
<b>2692.00</b>	* 79	0	.	.	.	105	78
<b>2713.00</b>	* 78	0	.	.	.	105	77
<b>2721.00</b>	* 77	0	.	.	.	105	76
<b>2769.00</b>	76	1	0.5891	0.4109	0.0332	106	75
<b>2772.00</b>	* 75	0	.	.	.	106	74
<b>2796.00</b>	74	1	0.5811	0.4189	0.0337	107	73

### Product-Limit Survival Estimates

<b>futime</b>	<b>Number at Risk</b>	<b>Observed Events</b>	<b>Survival</b>	<b>Failure</b>	<b>Survival Standard Error</b>	<b>Number Failed</b>	<b>Number Left</b>
<b>2797.00</b>	* 73	0	.	.	.	107	72
<b>2835.00</b>	* 72	0	.	.	.	107	71
<b>2847.00</b>	71	1	0.5729	0.4271	0.0342	108	70
<b>2863.00</b>	* 70	0	.	.	.	108	69
<b>2870.00</b>	* 69	0	.	.	.	108	68
<b>2891.00</b>	* 68	0	.	.	.	108	67
<b>2944.00</b>	* 67	0	.	.	.	108	66
<b>2976.00</b>	* 66	0	.	.	.	108	65
<b>2990.00</b>	* 65	0	.	.	.	108	64
<b>2995.00</b>	* 64	0	.	.	.	108	63
<b>3050.00</b>	* 63	0	.	.	.	108	62
<b>3059.00</b>	* 62	0	.	.	.	108	61
<b>3069.00</b>	* 61	0	.	.	.	108	60
<b>3086.00</b>	60	1	0.5634	0.4366	0.0349	109	59
<b>3090.00</b>	59	1	0.5538	0.4462	0.0356	110	58
<b>3092.00</b>	* 58	0	.	.	.	110	57
<b>3098.00</b>	* 57	0	.	.	.	110	56
<b>3099.00</b>	* 56	0	.	.	.	110	55
<b>3149.00</b>	* 55	0	.	.	.	110	54
<b>3150.00</b>	* 54	0	.	.	.	110	53
<b>3170.00</b>	53	1	0.5434	0.4566	0.0365	111	52
<b>3222.00</b>	52	1	0.5329	0.4671	0.0372	112	51
<b>3239.00</b>	* 51	0	.	.	.	112	50
<b>3244.00</b>	50	1	0.5223	0.4777	0.0380	113	49
<b>3255.00</b>	* 49	0	.	.	.	113	48
<b>3282.00</b>	48	1	0.5114	0.4886	0.0387	114	47
<b>3297.00</b>	* 47	0	.	.	.	114	46

### Product-Limit Survival Estimates

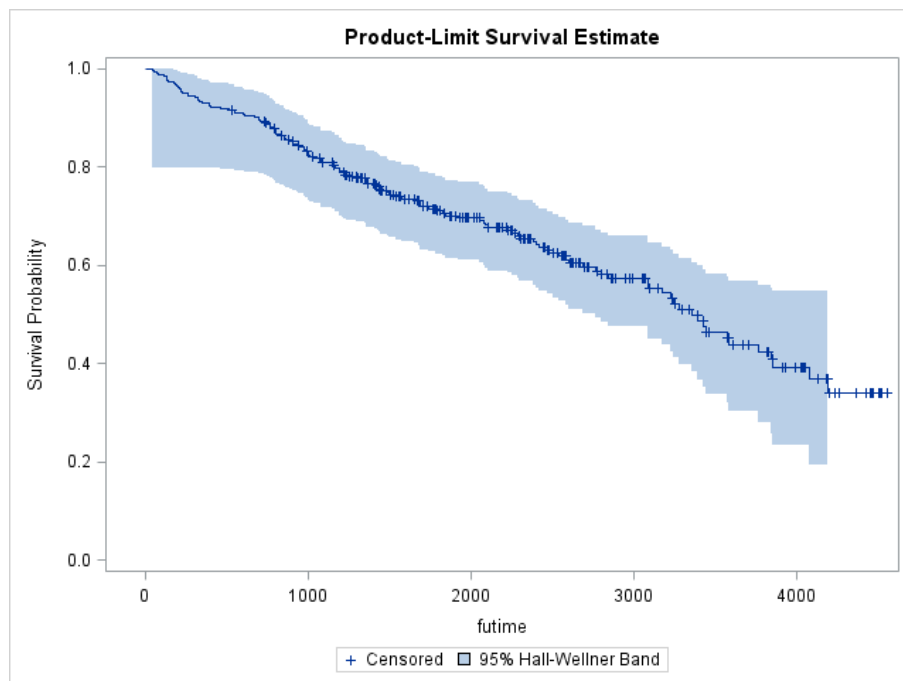
futime		Number at Risk	Observed Events	Survival	Failure	Survival Standard Error	Number Failed	Number Left
3336.00	*	46	0	.	.	.	114	45
3358.00		45	1	0.5000	0.5000	0.0395	115	44
3388.00	*	44	0	.	.	.	115	43
3395.00		43	1	0.4884	0.5116	0.0402	116	42
3422.00	*	42	0	.	.	.	116	41
3428.00		41	1	0.4765	0.5235	0.0410	117	40
3445.00		40	1	0.4646	0.5354	0.0417	118	39
3445.00	*	.	0	.	.	.	118	38
3458.00	*	38	0	.	.	.	118	37
3574.00		37	1	0.4520	0.5480	0.0424	119	36
3577.00	*	36	0	.	.	.	119	35
3581.00	*	35	0	.	.	.	119	34
3584.00		34	1	0.4387	0.5613	0.0432	120	33
3611.00	*	33	0	.	.	.	120	32
3672.00	*	32	0	.	.	.	120	31
3707.00	*	31	0	.	.	.	120	30
3762.00		30	1	0.4241	0.5759	0.0441	121	29
3820.00	*	29	0	.	.	.	121	28
3823.00	*	28	0	.	.	.	121	27
3839.00		27	1	0.4084	0.5916	0.0452	122	26
3850.00	*	26	0	.	.	.	122	25
3853.00		25	1	0.3921	0.6079	0.0463	123	24
3913.00	*	24	0	.	.	.	123	23
3933.00	*	23	0	.	.	.	123	22
3992.00	*	22	0	.	.	.	123	21
4025.00	*	21	0	.	.	.	123	20
4032.00	*	20	0	.	.	.	123	19

### Product-Limit Survival Estimates

futime		Number at Risk	Observed Events	Survival	Failure	Survival Standard Error	Number Failed	Number Left
4039.00	*	19	0	.	.	.	123	18
4050.00	*	18	0	.	.	.	123	17
4079.00		17	1	0.3690	0.6310	0.0490	124	16
4127.00	*	16	0	.	.	.	124	15
4184.00	*	15	0	.	.	.	124	14
4190.00	*	14	0	.	.	.	124	13
4191.00		13	1	0.3406	0.6594	0.0528	125	12
4196.00	*	12	0	.	.	.	125	11
4232.00	*	11	0	.	.	.	125	10
4256.00	*	10	0	.	.	.	125	9
4365.00	*	9	0	.	.	.	125	8
4427.00	*	8	0	.	.	.	125	7
4453.00	*	7	0	.	.	.	125	6
4459.00	*	6	0	.	.	.	125	5
4467.00	*	5	0	.	.	.	125	4
4500.00	*	4	0	.	.	.	125	3
4509.00	*	3	0	.	.	.	125	2
4523.00	*	2	0	.	.	.	125	1
4556.00	*	1	0	0.3406	0.6594	.	125	0

According to above table, we see the table of Kaplan-Meier estimates of the survival function produced by `proc lifetest`. Each row of the table corresponds to an interval of time, beginning at the time in the “FUTIME” column for that row, and ending just before the time in the “futime” column in the first subsequent row that has a different “futime” value. For example, the time interval represented by the first row is from 0 days to just before 1 day. In this interval, we can see that we had 312 people at risk and that no one died, as “Observed Events” equals 0 and the estimate of the “Survival” function is 1.0000. During the next interval, spanning from 1 day to just before 41 days, 1 people died, indicated by 1 rows of “futime” =41.00 and by “Observed Events” =1 in the last row where “futime” =41.00. It is important to note that the survival probabilities listed in the Survival column are unconditional and are to be interpreted as the

probability of surviving from the beginning of follow up time up to the number days in the futime column. From “futime” = 4196 to 4556, we see that there are several records where it appears no events occurred. These are indeed censored observations, further indicated by the “\*” appearing in the unlabeled second column. Subjects that are censored after a given time point contribute to the survival function until they drop out of the study but are not counted as a failure. We can see this reflected in the survival function estimate for “futime” =1350. During the interval [1350, 1360) 1 out of 214 subjects at-risk died, yielding a conditional probability of survival (the probability of survival in the given interval, given that the subject has survived up to the beginning of the interval) in this interval of  $(214-1)/214=0.9953$ . We see that the unconditional probability of surviving beyond 1350 days is 0.7742, since  $\hat{S}(1350) = 0.7742 = p(\text{surviving up to 1350 days}) \times 0.9953$ , we can solve for  $p(\text{surviving up to 1350 days}) = 0.7742/0.9953=0.7775$ . In the table above, we see that the probability surviving beyond 4191 days = 0.3406, the same probability as what we calculated for surviving up to 1350 days, which implies that the censored observations do not change the survival estimates when they leave the study, only the number at risk.



The step function form of the survival function is apparent in the graph of the Kaplan-Meier estimate. When a subject dies at a particular time point, the step function drops, whereas in between failure times the graph remains flat. The survival function drops most steeply at the beginning of study, suggesting that the hazard rate is highest immediately after hospitalization during the first 200 days. Censored observations are represented by vertical ticks on the graph. Notice the survival probability does not change when we encounter a censored observation. Because the observation with the longest follow-up is censored, the survival function will not reach 0. Instead, the survival function will remain at the survival probability estimated at the previous interval. The survival

function is undefined past this final interval at 2358 days. The blue-shaded area around the survival curve represents the 95% confidence band, here Hall-Wellner confidence bands. This confidence band is calculated for the entire survival function, and at any given interval must be wider than the pointwise confidence interval (the confidence interval around a single interval) to ensure that 95% of all pointwise confidence intervals are contained within this band. Many transformations of the survivor function are available for alternate ways of calculating confidence intervals through the `conftype` option, though most transformations should yield very similar confidence intervals.

### Survival Function and Cumulative Hazard Rate

fuptime	Product-Limit					Nelson-Aalen			Number Failed	Number Left
	Number at Risk	Observed Events	Survival	Failure	Survival Standard Error	Cumulative Hazard	Cum Haz Standard Error			
0.00	312	0	1.0000	0	0	0	.	0	312	
41.00	312	1	0.9968	0.00321	0.00320	0.00321	0.00321	1	311	
51.00	311	1	0.9936	0.00641	0.00452	0.00642	0.00454	2	310	
71.00	310	1	0.9904	0.00962	0.00552	0.00965	0.00557	3	309	
77.00	309	1	0.9872	0.0128	0.00637	0.0129	0.00644	4	308	
110.00	308	1	0.9840	0.0160	0.00711	0.0161	0.00721	5	307	
130.00	307	1	0.9808	0.0192	0.00778	0.0194	0.00791	6	306	
131.00	306	1	0.9776	0.0224	0.00838	0.0227	0.00856	7	305	
140.00	305	1	0.9744	0.0256	0.00895	0.0259	0.00917	8	304	
179.00	304	1	0.9712	0.0288	0.00948	0.0292	0.00974	9	303	
186.00	303	1	0.9679	0.0321	0.00997	0.0325	0.0103	10	302	
191.00	302	1	0.9647	0.0353	0.0104	0.0358	0.0108	11	301	
198.00	301	1	0.9615	0.0385	0.0109	0.0392	0.0113	12	300	
207.00	300	1	0.9583	0.0417	0.0113	0.0425	0.0118	13	299	
216.00	299	1	0.9551	0.0449	0.0117	0.0458	0.0123	14	298	
223.00	298	1	0.9519	0.0481	0.0121	0.0492	0.0127	15	297	
264.00	.	.	.	.	.	.	.	16	296	
264.00	297	2	0.9455	0.0545	0.0129	0.0559	0.0136	17	295	
304.00	295	1	0.9423	0.0577	0.0132	0.0593	0.0140	18	294	



### Survival Function and Cumulative Hazard Rate

fuptime	Product-Limit					Nelson-Aalen			
	Number at Risk	Observed Events	Survival	Failure	Survival Standard Error	Cumulative Hazard	Cum Haz Standard Error	Number Failed	Number Left
<b>321.00</b>	294	1	0.9391	0.0609	0.0135	0.0627	0.0144	19	293
<b>326.00</b>	293	1	0.9359	0.0641	0.0139	0.0661	0.0148	20	292
<b>334.00</b>	292	1	0.9327	0.0673	0.0142	0.0696	0.0152	21	291
<b>348.00</b>	291	1	0.9295	0.0705	0.0145	0.0730	0.0156	22	290
<b>388.00</b>	290	1	0.9263	0.0737	0.0148	0.0764	0.0159	23	289
<b>400.00</b>	289	1	0.9231	0.0769	0.0151	0.0799	0.0163	24	288
<b>460.00</b>	288	1	0.9199	0.0801	0.0154	0.0834	0.0167	25	287
<b>515.00</b>	287	1	0.9167	0.0833	0.0156	0.0869	0.0170	26	286
<b>533.00</b>	* 286	0	.	.	.	.	.	26	285
<b>549.00</b>	285	1	0.9135	0.0865	0.0159	0.0904	0.0174	27	284
<b>552.00</b>	284	1	0.9102	0.0898	0.0162	0.0939	0.0177	28	283
<b>597.00</b>	283	1	0.9070	0.0930	0.0164	0.0974	0.0181	29	282
<b>611.00</b>	282	1	0.9038	0.0962	0.0167	0.1010	0.0184	30	281
<b>673.00</b>	281	1	0.9006	0.0994	0.0169	0.1045	0.0188	31	280
<b>694.00</b>	280	1	0.8974	0.1026	0.0172	0.1081	0.0191	32	279
<b>708.00</b>	279	1	0.8942	0.1058	0.0174	0.1117	0.0195	33	278
<b>732.00</b>	* 278	0	.	.	.	.	.	33	277
<b>733.00</b>	277	1	0.8909	0.1091	0.0177	0.1153	0.0198	34	276
<b>737.00</b>	* 276	0	.	.	.	.	.	34	275
<b>750.00</b>	275	1	0.8877	0.1123	0.0179	0.1189	0.0201	35	274
<b>762.00</b>	274	1	0.8844	0.1156	0.0181	0.1226	0.0204	36	273
<b>769.00</b>	273	1	0.8812	0.1188	0.0183	0.1262	0.0208	37	272
<b>786.00</b>	272	1	0.8780	0.1220	0.0186	0.1299	0.0211	38	271
<b>788.00</b>	* 271	0	.	.	.	.	.	38	270
<b>790.00</b>	270	1	0.8747	0.1253	0.0188	0.1336	0.0214	39	269

### Survival Function and Cumulative Hazard Rate

fuptime	Product-Limit					Nelson-Aalen			
	Number at Risk	Observed Events	Survival	Failure	Survival Standard Error	Cumulative Hazard	Cum Haz Standard Error	Number Failed	Number Left
<b>797.00</b>	269	1	0.8715	0.1285	0.0190	0.1373	0.0217	40	268
<b>799.00</b>	268	1	0.8682	0.1318	0.0192	0.1411	0.0221	41	267
<b>824.00</b>	267	1	0.8650	0.1350	0.0194	0.1448	0.0224	42	266
<b>837.00</b> *	266	0	.	.	.	.	.	42	265
<b>839.00</b> *	265	0	.	.	.	.	.	42	264
<b>850.00</b>	264	1	0.8617	0.1383	0.0196	0.1486	0.0227	43	263
<b>853.00</b>	263	1	0.8584	0.1416	0.0198	0.1524	0.0230	44	262
<b>859.00</b>	262	1	0.8551	0.1449	0.0200	0.1562	0.0233	45	261
<b>877.00</b> *	261	0	.	.	.	.	.	45	260
<b>890.00</b>	260	1	0.8518	0.1482	0.0202	0.1601	0.0236	46	259
<b>901.00</b> *	259	0	.	.	.	.	.	46	258
<b>904.00</b>	258	1	0.8485	0.1515	0.0204	0.1639	0.0239	47	257
<b>930.00</b>	257	1	0.8452	0.1548	0.0205	0.1678	0.0243	48	256
<b>939.00</b> *	256	0	.	.	.	.	.	48	255
<b>943.00</b>	255	1	0.8419	0.1581	0.0207	0.1718	0.0246	49	254
<b>971.00</b>	254	1	0.8386	0.1614	0.0209	0.1757	0.0249	50	253
<b>974.00</b>	253	1	0.8353	0.1647	0.0211	0.1796	0.0252	51	252
<b>980.00</b>	252	1	0.8320	0.1680	0.0213	0.1836	0.0255	52	251
<b>994.00</b> *	251	0	.	.	.	.	.	52	250
<b>999.00</b>	250	1	0.8287	0.1713	0.0214	0.1876	0.0258	53	249
<b>1000.00</b>	249	1	0.8253	0.1747	0.0216	0.1916	0.0261	54	248
<b>1012.00</b>	248	1	0.8220	0.1780	0.0218	0.1957	0.0264	55	247
<b>1030.00</b> *	247	0	.	.	.	.	.	55	246
<b>1037.00</b>	246	1	0.8187	0.1813	0.0219	0.1997	0.0268	56	245
<b>1067.00</b> *	245	0	.	.	.	.	.	56	244

### Survival Function and Cumulative Hazard Rate

fuptime	Product-Limit					Nelson-Aalen		Number Failed	Number Left
	Number at Risk	Observed Events	Survival	Failure	Survival Standard Error	Cumulative Hazard	Cum Haz Standard Error		
1077.00	244	1	0.8153	0.1847	0.0221	0.2038	0.0271	57	243
1080.00	243	1	0.8119	0.1881	0.0223	0.2079	0.0274	58	242
1083.00	242	1	0.8086	0.1914	0.0224	0.2121	0.0277	59	241
1084.00 *	241	0	.	.	.	.	.	59	240
1149.00 *	240	0	.	.	.	.	.	59	239
1152.00	239	1	0.8052	0.1948	0.0226	0.2163	0.0280	60	238
1153.00 *	238	0	.	.	.	.	.	60	237
1165.00	237	1	0.8018	0.1982	0.0227	0.2205	0.0283	61	236
1170.00	236	1	0.7984	0.2016	0.0229	0.2247	0.0286	62	235
1191.00	.	.	.	.	.	.	.	63	234
1191.00	235	2	0.7916	0.2084	0.0232	0.2332	0.0293	64	233
1212.00	233	1	0.7882	0.2118	0.0234	0.2375	0.0296	65	232
1216.00 *	.	0	.	.	.	.	.	65	231
1216.00 *	232	0	.	.	.	.	.	65	230
1217.00	230	1	0.7848	0.2152	0.0235	0.2419	0.0299	66	229
1230.00 *	229	0	.	.	.	.	.	66	228
1234.00 *	228	0	.	.	.	.	.	66	227
1235.00	227	1	0.7813	0.2187	0.0237	0.2463	0.0302	67	226
1250.00 *	226	0	.	.	.	.	.	67	225
1271.00 *	225	0	.	.	.	.	.	67	224
1293.00 *	224	0	.	.	.	.	.	67	223
1295.00 *	223	0	.	.	.	.	.	67	222
1297.00	222	1	0.7778	0.2222	0.0238	0.2508	0.0305	68	221
1300.00 *	221	0	.	.	.	.	.	68	220
1301.00 *	220	0	.	.	.	.	.	68	219

### Survival Function and Cumulative Hazard Rate

fuptime		Number at Risk	Observed Events	Product-Limit		Nelson-Aalen		Number Failed	Number Left
				Survival	Failure Standard Error	Cumulative Hazard	Cum Haz Standard Error		
1302.00	* 219	0	.	.	.	.	.	68	218
1320.00	* 218	0	.	.	.	.	.	68	217
1321.00	* 217	0	.	.	.	.	.	68	216
1329.00	* 216	0	.	.	.	.	.	68	215
1349.00	* 215	0	.	.	.	.	.	68	214
1350.00	214	1	0.7742	0.2258	0.0240	0.2554	0.0309	69	213
1356.00	213	1	0.7705	0.2295	0.0241	0.2601	0.0313	70	212
1360.00	212	1	0.7669	0.2331	0.0243	0.2649	0.0316	71	211
1363.00	* .	0	.	.	.	.	.	71	210
1363.00	* 211	0	.	.	.	.	.	71	209
1401.00	* 209	0	.	.	.	.	.	71	208
1408.00	* 208	0	.	.	.	.	.	71	207
1412.00	* 207	0	.	.	.	.	.	71	206
1413.00	206	1	0.7632	0.2368	0.0245	0.2697	0.0320	72	205
1418.00	* 205	0	.	.	.	.	.	72	204
1420.00	* 204	0	.	.	.	.	.	72	203
1427.00	203	1	0.7594	0.2406	0.0246	0.2746	0.0324	73	202
1433.00	* 202	0	.	.	.	.	.	73	201
1434.00	201	1	0.7556	0.2444	0.0248	0.2796	0.0327	74	200
1434.00	* .	0	.	.	.	.	.	74	199
1435.00	* 199	0	.	.	.	.	.	74	198
1444.00	198	1	0.7518	0.2482	0.0250	0.2847	0.0331	75	197
1447.00	* 197	0	.	.	.	.	.	75	196
1455.00	* 196	0	.	.	.	.	.	75	195
1457.00	* 195	0	.	.	.	.	.	75	194

### Survival Function and Cumulative Hazard Rate

fuptime		Number at Risk	Observed Events	Product-Limit		Nelson-Aalen		Number Failed	Number Left
				Survival	Failure	Survival Standard Error	Cumulative Hazard	Cum Haz Standard Error	
1481.00	*	194	0	.	.	.	.	.	75
1487.00		193	1	0.7479	0.2521	0.0251	0.2898	0.0335	76
1492.00		192	1	0.7440	0.2560	0.0253	0.2951	0.0339	77
1504.00	*	191	0	.	.	.	.	.	77
1525.00	*	190	0	.	.	.	.	.	77
1536.00		189	1	0.7401	0.2599	0.0255	0.3003	0.0343	78
1542.00	*	188	0	.	.	.	.	.	78
1558.00	*	187	0	.	.	.	.	.	78
1568.00	*	186	0	.	.	.	.	.	78
1569.00	*	185	0	.	.	.	.	.	78
1576.00		184	1	0.7361	0.2639	0.0256	0.3058	0.0348	79
1592.00	*	183	0	.	.	.	.	.	79
1614.00	*	.	0	.	.	.	.	.	79
1614.00	*	182	0	.	.	.	.	.	79
1615.00	*	180	0	.	.	.	.	.	79
1656.00	*	179	0	.	.	.	.	.	79
1657.00		178	1	0.7319	0.2681	0.0258	0.3114	0.0352	80
1666.00	*	177	0	.	.	.	.	.	80
1677.00	*	176	0	.	.	.	.	.	80
1682.00		175	1	0.7278	0.2722	0.0260	0.3171	0.0357	81
1690.00	.	.	.	.	.	.	.	.	82
1690.00		174	2	0.7194	0.2806	0.0264	0.3286	0.0366	83
1701.00	*	172	0	.	.	.	.	.	83
1702.00	*	171	0	.	.	.	.	.	83
1735.00	*	170	0	.	.	.	.	.	83

### Survival Function and Cumulative Hazard Rate

fuptime	Product-Limit					Nelson-Aalen		Number Failed	Number Left
	Number at Risk	Observed Events	Survival	Failure	Survival Standard Error	Cumulative Hazard	Cum Haz Standard Error		
1741.00	169	1	0.7151	0.2849	0.0266	0.3345	0.0371	84	168
1765.00 *	168	0	.	.	.	.	.	84	167
1769.00 *	167	0	.	.	.	.	.	84	166
1770.00 *	166	0	.	.	.	.	.	84	165
1776.00 *	165	0	.	.	.	.	.	84	164
1783.00 *	164	0	.	.	.	.	.	84	163
1785.00 *	163	0	.	.	.	.	.	84	162
1786.00	162	1	0.7107	0.2893	0.0268	0.3407	0.0376	85	161
1790.00 *	161	0	.	.	.	.	.	85	160
1810.00 *	160	0	.	.	.	.	.	85	159
1827.00	159	1	0.7063	0.2937	0.0270	0.3470	0.0381	86	158
1831.00 *	158	0	.	.	.	.	.	86	157
1832.00 *	157	0	.	.	.	.	.	86	156
1847.00	156	1	0.7017	0.2983	0.0272	0.3534	0.0386	87	155
1874.00 *	155	0	.	.	.	.	.	87	154
1882.00 *	.	0	.	.	.	.	.	87	153
1882.00 *	154	0	.	.	.	.	.	87	152
1908.00 *	152	0	.	.	.	.	.	87	151
1925.00	151	1	0.6971	0.3029	0.0274	0.3600	0.0392	88	150
1932.00 *	150	0	.	.	.	.	.	88	149
1945.00 *	149	0	.	.	.	.	.	88	148
1951.00 *	148	0	.	.	.	.	.	88	147
1967.00 *	147	0	.	.	.	.	.	88	146
1978.00 *	146	0	.	.	.	.	.	88	145
1979.00 *	145	0	.	.	.	.	.	88	144

### Survival Function and Cumulative Hazard Rate

fuptime	Product-Limit					Nelson-Aalen			
	Number at Risk	Observed Events	Survival	Failure	Survival Standard Error	Cumulative Hazard	Cum Haz Standard Error	Number Failed	Number Left
2022.00	* 144	0	.	.	.	.	.	88	143
2033.00	* 143	0	.	.	.	.	.	88	142
2050.00	* 142	0	.	.	.	.	.	88	141
2055.00	141	1	0.6921	0.3079	0.0276	0.3671	0.0398	89	140
2081.00	140	1	0.6872	0.3128	0.0279	0.3743	0.0405	90	139
2090.00	139	1	0.6823	0.3177	0.0281	0.3814	0.0411	91	138
2105.00	138	1	0.6773	0.3227	0.0283	0.3887	0.0417	92	137
2106.00	* 137	0	.	.	.	.	.	92	136
2157.00	* 136	0	.	.	.	.	.	92	135
2168.00	* 135	0	.	.	.	.	.	92	134
2170.00	* 134	0	.	.	.	.	.	92	133
2171.00	* 133	0	.	.	.	.	.	92	132
2176.00	* 132	0	.	.	.	.	.	92	131
2178.00	* 131	0	.	.	.	.	.	92	130
2195.00	* 130	0	.	.	.	.	.	92	129
2216.00	* 129	0	.	.	.	.	.	92	128
2221.00	* 128	0	.	.	.	.	.	92	127
2224.00	127	1	0.6720	0.3280	0.0286	0.3966	0.0425	93	126
2224.00	* .	0	.	.	.	.	.	93	125
2241.00	* 125	0	.	.	.	.	.	93	124
2255.00	* 124	0	.	.	.	.	.	93	123
2256.00	123	1	0.6665	0.3335	0.0289	0.4047	0.0432	94	122
2272.00	* 122	0	.	.	.	.	.	94	121
2288.00	121	1	0.6610	0.3390	0.0292	0.4130	0.0440	95	120
2294.00	* 120	0	.	.	.	.	.	95	119

### Survival Function and Cumulative Hazard Rate

fuptime	Product-Limit					Nelson-Aalen		Number Failed	Number Left
	Number at Risk	Observed Events	Survival	Failure	Survival Standard Error	Cumulative Hazard	Cum Haz Standard Error		
2297.00	119	1	0.6554	0.3446	0.0295	0.4214	0.0448	96	118
2301.00 *	118	0	.	.	.	.	.	96	117
2318.00 *	117	0	.	.	.	.	.	96	116
2330.00 *	116	0	.	.	.	.	.	96	115
2332.00 *	115	0	.	.	.	.	.	96	114
2350.00 *	114	0	.	.	.	.	.	96	113
2357.00 *	113	0	.	.	.	.	.	96	112
2363.00 *	112	0	.	.	.	.	.	96	111
2365.00 *	111	0	.	.	.	.	.	96	110
2386.00	110	1	0.6495	0.3505	0.0298	0.4305	0.0457	97	109
2400.00	109	1	0.6435	0.3565	0.0301	0.4396	0.0466	98	108
2419.00	108	1	0.6376	0.3624	0.0304	0.4489	0.0476	99	107
2443.00 *	107	0	.	.	.	.	.	99	106
2449.00 *	106	0	.	.	.	.	.	99	105
2452.00 *	105	0	.	.	.	.	.	99	104
2456.00 *	104	0	.	.	.	.	.	99	103
2466.00	103	1	0.6314	0.3686	0.0307	0.4586	0.0485	100	102
2468.00 *	102	0	.	.	.	.	.	100	101
2475.00 *	101	0	.	.	.	.	.	100	100
2503.00	100	1	0.6251	0.3749	0.0311	0.4686	0.0496	101	99
2504.00 *	.	0	.	.	.	.	.	101	98
2504.00 *	99	0	.	.	.	.	.	101	97
2527.00 *	97	0	.	.	.	.	.	101	96
2540.00	96	1	0.6186	0.3814	0.0314	0.4790	0.0506	102	95
2555.00 *	95	0	.	.	.	.	.	102	94



### Survival Function and Cumulative Hazard Rate

fuptime	Product-Limit					Nelson-Aalen		Number Failed	Number Left
	Number at Risk	Observed Events	Survival	Failure	Survival Standard Error	Cumulative Hazard	Cum Haz Standard Error		
2556.00	* 94	0	.	.	.	.	.	102	93
2563.00	* 93	0	.	.	.	.	.	102	92
2573.00	* 92	0	.	.	.	.	.	102	91
2574.00	* 91	0	.	.	.	.	.	102	90
2576.00	* 90	0	.	.	.	.	.	102	89
2580.00	* 89	0	.	.	.	.	.	102	88
2583.00	88	1	0.6115	0.3885	0.0318	0.4904	0.0519	103	87
2598.00	87	1	0.6045	0.3955	0.0322	0.5019	0.0532	104	86
2609.00	* 86	0	.	.	.	.	.	104	85
2615.00	* 85	0	.	.	.	.	.	104	84
2624.00	* 84	0	.	.	.	.	.	104	83
2644.00	* 83	0	.	.	.	.	.	104	82
2657.00	* 82	0	.	.	.	.	.	104	81
2666.00	* 81	0	.	.	.	.	.	104	80
2689.00	80	1	0.5969	0.4031	0.0327	0.5144	0.0546	105	79
2692.00	* 79	0	.	.	.	.	.	105	78
2713.00	* 78	0	.	.	.	.	.	105	77
2721.00	* 77	0	.	.	.	.	.	105	76
2769.00	76	1	0.5891	0.4109	0.0332	0.5275	0.0562	106	75
2772.00	* 75	0	.	.	.	.	.	106	74
2796.00	74	1	0.5811	0.4189	0.0337	0.5410	0.0578	107	73
2797.00	* 73	0	.	.	.	.	.	107	72
2835.00	* 72	0	.	.	.	.	.	107	71
2847.00	71	1	0.5729	0.4271	0.0342	0.5551	0.0595	108	70
2863.00	* 70	0	.	.	.	.	.	108	69

### Survival Function and Cumulative Hazard Rate

fuptime	Product-Limit					Nelson-Aalen		Number Failed	Number Left
	Number at Risk	Observed Events	Survival	Failure	Survival Standard Error	Cumulative Hazard	Cum Haz Standard Error		
2870.00	* 69	0	.	.	.	.	.	108	68
2891.00	* 68	0	.	.	.	.	.	108	67
2944.00	* 67	0	.	.	.	.	.	108	66
2976.00	* 66	0	.	.	.	.	.	108	65
2990.00	* 65	0	.	.	.	.	.	108	64
2995.00	* 64	0	.	.	.	.	.	108	63
3050.00	* 63	0	.	.	.	.	.	108	62
3059.00	* 62	0	.	.	.	.	.	108	61
3069.00	* 61	0	.	.	.	.	.	108	60
3086.00	60	1	0.5634	0.4366	0.0349	0.5718	0.0618	109	59
3090.00	59	1	0.5538	0.4462	0.0356	0.5887	0.0640	110	58
3092.00	* 58	0	.	.	.	.	.	110	57
3098.00	* 57	0	.	.	.	.	.	110	56
3099.00	* 56	0	.	.	.	.	.	110	55
3149.00	* 55	0	.	.	.	.	.	110	54
3150.00	* 54	0	.	.	.	.	.	110	53
3170.00	53	1	0.5434	0.4566	0.0365	0.6076	0.0668	111	52
3222.00	52	1	0.5329	0.4671	0.0372	0.6268	0.0695	112	51
3239.00	* 51	0	.	.	.	.	.	112	50
3244.00	50	1	0.5223	0.4777	0.0380	0.6468	0.0723	113	49
3255.00	* 49	0	.	.	.	.	.	113	48
3282.00	48	1	0.5114	0.4886	0.0387	0.6677	0.0752	114	47
3297.00	* 47	0	.	.	.	.	.	114	46
3336.00	* 46	0	.	.	.	.	.	114	45
3358.00	45	1	0.5000	0.5000	0.0395	0.6899	0.0785	115	44

### Survival Function and Cumulative Hazard Rate

fuptime	Product-Limit					Nelson-Aalen			
	Number at Risk	Observed Events	Survival	Failure	Survival Standard Error	Cumulative Hazard	Cum Haz Standard Error	Number Failed	Number Left
3388.00 *	44	0	.	.	.	.	.	115	43
3395.00	43	1	0.4884	0.5116	0.0402	0.7132	0.0818	116	42
3422.00 *	42	0	.	.	.	.	.	116	41
3428.00	41	1	0.4765	0.5235	0.0410	0.7375	0.0854	117	40
3445.00	40	1	0.4646	0.5354	0.0417	0.7625	0.0890	118	39
3445.00 *	.	0	.	.	.	.	.	118	38
3458.00 *	38	0	.	.	.	.	.	118	37
3574.00	37	1	0.4520	0.5480	0.0424	0.7896	0.0930	119	36
3577.00 *	36	0	.	.	.	.	.	119	35
3581.00 *	35	0	.	.	.	.	.	119	34
3584.00	34	1	0.4387	0.5613	0.0432	0.8190	0.0975	120	33
3611.00 *	33	0	.	.	.	.	.	120	32
3672.00 *	32	0	.	.	.	.	.	120	31
3707.00 *	31	0	.	.	.	.	.	120	30
3762.00	30	1	0.4241	0.5759	0.0441	0.8523	0.1031	121	29
3820.00 *	29	0	.	.	.	.	.	121	28
3823.00 *	28	0	.	.	.	.	.	121	27
3839.00	27	1	0.4084	0.5916	0.0452	0.8894	0.1095	122	26
3850.00 *	26	0	.	.	.	.	.	122	25
3853.00	25	1	0.3921	0.6079	0.0463	0.9294	0.1166	123	24
3913.00 *	24	0	.	.	.	.	.	123	23
3933.00 *	23	0	.	.	.	.	.	123	22
3992.00 *	22	0	.	.	.	.	.	123	21
4025.00 *	21	0	.	.	.	.	.	123	20
4032.00 *	20	0	.	.	.	.	.	123	19

### Survival Function and Cumulative Hazard Rate

fuptime		Number at Risk	Observed Events	Product-Limit		Nelson-Aalen			Number Failed	Number Left
				Survival	Failure	Survival Standard Error	Cumulative Hazard	Cum Haz Standard Error		
4039.00	*	19	0	.	.	.	.	.	123	18
4050.00	*	18	0	.	.	.	.	.	123	17
4079.00		17	1	0.3690	0.6310	0.0490	0.9882	0.1306	124	16
4127.00	*	16	0	.	.	.	.	.	124	15
4184.00	*	15	0	.	.	.	.	.	124	14
4190.00	*	14	0	.	.	.	.	.	124	13
4191.00		13	1	0.3406	0.6594	0.0528	1.0651	0.1516	125	12
4196.00	*	12	0	.	.	.	.	.	125	11
4232.00	*	11	0	.	.	.	.	.	125	10
4256.00	*	10	0	.	.	.	.	.	125	9
4365.00	*	9	0	.	.	.	.	.	125	8
4427.00	*	8	0	.	.	.	.	.	125	7
4453.00	*	7	0	.	.	.	.	.	125	6
4459.00	*	6	0	.	.	.	.	.	125	5
4467.00	*	5	0	.	.	.	.	.	125	4
4500.00	*	4	0	.	.	.	.	.	125	3
4509.00	*	3	0	.	.	.	.	.	125	2
4523.00	*	2	0	.	.	.	.	.	125	1
4556.00	*	1	0	0.3406	0.6594	.	.	.	125	0

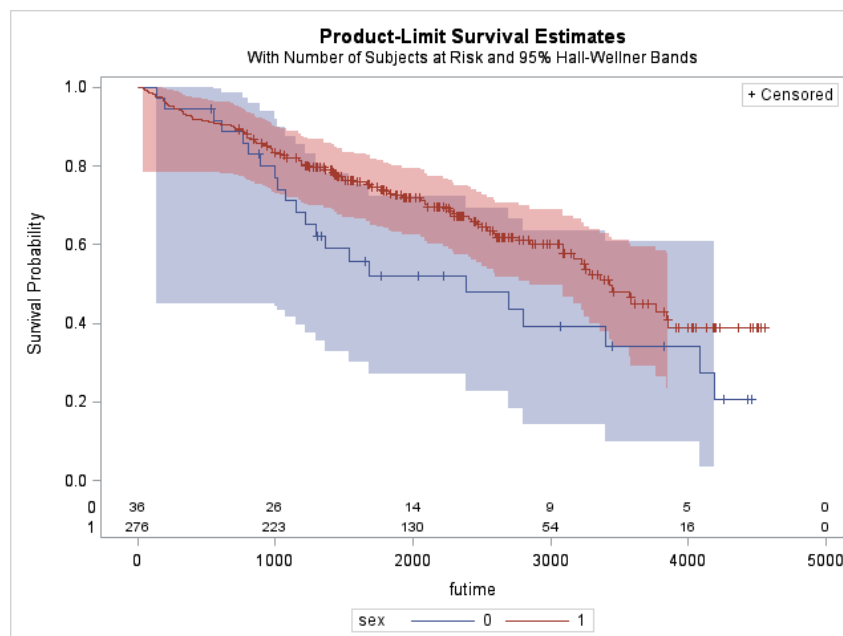
The Nelson-Aalen estimator is requested in SAS through the nelson option on the `proc lifetest` statement. SAS will output both Kaplan Meier estimates of the survival function and Nelson-Aalen estimates of the cumulative hazard function in one table. Researchers are often interested in estimates of survival time at which 50% or 25% of the population have died or failed. Because of the positive skew often seen with follow-up-times, medians are often a better indicator of an “average” survival time. We obtain estimates of these quartiles as well as estimates of the mean survival time by default from `proc lifetest`. We see that beyond 3395 days, 50% of the

population is expected to have failed. Notice that the interval during which the first 25% of the population is expected to fail, [0,1170) is much shorter than the interval during which the second 25% of the population is expected to fail, [1170,1925). This reinforces our suspicion that the hazard of failure is greater during the beginning of follow-up time.

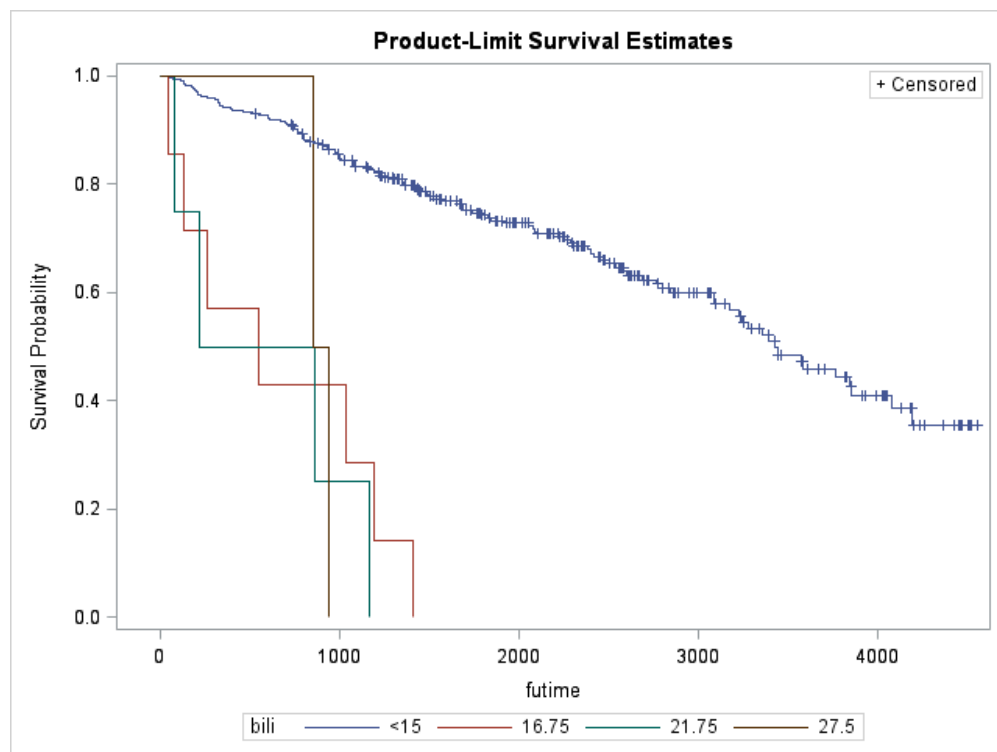
Summary Statistics for Time Variable futime

Quartile Estimates				
Percent	Point Estimate	95% Confidence Interval Transform	[Lower	Upper)
75	.	LOGLOG	4191.00	.
50	3395.00	LOGLOG	3086.00	3839.00
25	1487.00	LOGLOG	1170.00	1925.00

Suppose that you suspect that the survival function is not the same among some of the groups in your study (some groups tend to fail more quickly than others). One can also use non-parametric methods to test for equality of the survival function among groups in the following manner: When provided with a grouping variable in a strata statement in `proc lifetest`, SAS will produce graphs of the survival function (unless other graphs are requested) stratified by the grouping variable as well as tests of equality of the survival function across strata. For example, we could enter the class (categorical) variable gender on the strata statement to request that SAS compare the survival experiences of males and females. In the graph of the Kaplan-Meier estimator stratified by gender below, it appears that females generally have a worse survival experience. This is reinforced by the three significant tests of equality.



We request plots of the hazard function with a bandwidth of 200 days with `plot=hazard (bw=200)` . SAS conveniently allows the creation of strata from a continuous variable, such as `bili`, on the fly with the `strata` statement We specify the left endpoints of each `bili` to form 5 `bili` categories: 15-18.5, 18.5-25, 25-30, 30-40, and >40. The lines in the graph are labeled by the midpoint `bili` in each group. From the plot we can see that the hazard function indeed appears higher at the beginning of follow-up time and then decreases until it levels off at around 312 days and stays low and mostly constant. The hazard function is also generally higher for the two lowest `bili` categories. The sudden upticks at the end of follow-up time are not to be trusted, as they are likely due to the few number of subjects at risk at the end. The red curve representing the lowest `bili` category is truncated on the right because the last person in that group died long before the end of follow-up time.



Next, we are going to fitting a simple Cox regression model for this data. We request Cox regression through `proc phreg` in SAS. Previously, we graphed the survival functions of males in females in our study dataset and suspected that the survival experience after Primary Biliary Cirrhosis may be different between the two genders. Perhaps you also suspect that the hazard rate changes with age as well. Below we demonstrate a simple model in `proc phreg`, where we determine the effects of categorical predictors `drug`, `sex`, presence of ascites, presence of hepatomegaly, presence of spiders, presence of edema and continuous predictors, serum bilirubin, serum cholesterol, albumin, urine copper, alkaline phosphatase, SGOT , triglicerides, platelets per

cubic, prothrombin time, histologic stage of disease on the hazard rate. We also would like survival curves based on our model, so we add `plots=survival` to the `proc phreg` statement, although as we shall see this specification is probably insufficient for what we want. On the model statement, on the left side of the equation, we provide the follow up time variable, `futime`, and the censoring variable, `status`, with all censoring values listed in parentheses. On the right side of the equation we list all the predictors.

Model Fit Statistics		
Criterion	Without Covariates	With Covariates
<b>-2 LOG L</b>	1100.404	931.853
<b>AIC</b>	1100.404	967.853
<b>SBC</b>	1100.404	1016.624

Testing Global Null Hypothesis: BETA=0			
Test	Chi-Square	DF	Pr > ChiSq
<b>Likelihood Ratio</b>	168.5510	18	<.0001
<b>Score</b>	295.0615	18	<.0001
<b>Wald</b>	175.8240	18	<.0001

#### Analysis of Maximum Likelihood Estimates

Parameter	DF	Parameter Estimate	Standard Error	Chi-Square	Pr > ChiSq	Hazard Ratio	Label
<b>drug</b>	<b>1</b>	0.17161	0.21919	0.6130	0.4337	1.187	drug 1
<b>age</b>	1	0.02946	0.01163	6.4159	0.0113	1.030	
<b>sex</b>	<b>0</b>	0.35228	0.30959	1.2948	0.2552	1.422	sex 0
<b>ascites</b>	<b>0</b>	-0.01492	0.39051	0.0015	0.9695	0.985	ascites 0
<b>hepato</b>	<b>0</b>	-0.05806	0.25243	0.0529	0.8181	0.944	hepato 0
<b>spiders</b>	<b>0</b>	-0.06719	0.24878	0.0729	0.7871	0.935	spiders 0
<b>edema</b>	<b>0</b>	-1.15034	0.41561	7.6608	0.0056	0.317	edema 0
<b>edema</b>	<b>0.5</b>	-0.89570	0.44874	3.9841	0.0459	0.408	edema 0.5
<b>bili</b>	1	0.08026	0.02619	9.3892	0.0022	1.084	
<b>chol</b>	1	0.0004901	0.0004461	1.2069	0.2719	1.000	
<b>albumin</b>	1	-0.75003	0.30613	6.0026	0.0143	0.472	
<b>copper</b>	1	0.00240	0.00116	4.2510	0.0392	1.002	

Parameter	DF	Parameter Estimate	Standard Error	Chi-Square	Pr > ChiSq	Hazard Ratio	Label
<b>alk_phos</b>	1	3.12933E-6	0.0000395	0.0063	0.9369	1.000	
<b>sgot</b>	1	0.00386	0.00198	3.7996	0.0513	1.004	
<b>trig</b>	1	-0.0005576	0.00143	0.1524	0.6962	0.999	
<b>platelet</b>	1	0.0007971	0.00119	0.4474	0.5036	1.001	
<b>protime</b>	1	0.24125	0.10680	5.1029	0.0239	1.273	
<b>stage</b>	1	0.44957	0.17468	6.6237	0.0101	1.568	

The above output is only a portion of what SAS produces each time we run `proc phreg`. In particular we would like to highlight the previous tables: Displays fit statistics which are typically used for model comparison and selection. This is our first model, so we have no other model to compare with, except that by default SAS will display model fit statistics of a model with no predictors. We see here that adding gender and particularly age (as we will see below) as predictors improves the fit of the model, as all three statistics decrease. According to testing Global Null Hypothesis, Displays test of hypothesis that all coefficients in the model are 0, that is, an overall test of whether the model as a whole can predict changes in the hazard rate. These tests are asymptotically equivalent, but may differ in smaller samples, in which case the likelihood ratio test is generally preferred. Here the tests agree, and it appears that at least one of our regression coefficients is significantly different from 0. Based on the Analysis of Maximum Likelihood Estimates, Displays model coefficients, tests of significance, and exponential coefficient as hazard ratio. Here it appears that although females have a ~35% (Hazard Ratio = 1.422) increase in the hazard rate compared to males, this decrease is not significant. On the other hand, with each year of age the hazard rate increases by 3% (Hazard Ratio = 1.030), a significant change. Our initial suspicion that the hazard rates were different between genders seems to be wrong once we account for age effects (females are generally older in this dataset), but as shall see the effects are more nuanced. Also notice that there is no intercept. In Cox regression, the intercept is absorbed into the baseline hazard function, which is left unspecified.

## 6. Conclusions and Future works

According to our sas output, we could know that the covariates AIC values of with covariates is smaller than without covariates and also based on the p values of MLE table, serum bilirubin and Presence of edema have too low values, so these are definitely significant variables. So we can improve our model fitting, remove that significant variables and refit the model. However in this study just we are discussing overall survival analysis and also we discussed cox model fitting. Although many others prefer the type of Cox's PH to more than Zhu M. and Fan G. (2006), there are various factors besides the immune system that affects the lives of patients still. In our last



model. This means that we may leave some information about PBC data not to consider and we could adjust by integrating covariates. Additionally, we do not apply the AFT model to the data that defines time based on covariates. This has a similar procedure, a stressful step that leads to economic growth, which is useful in evaluating the time based on covariates and trust. Secondly, there are many things that are not missing in the PBC data and removing all the documents includes lack of data. But we can consider the arguments that can be attributed to the example of an argument inverse probability weighted (AIPW) by Wang and Chen (2001). When you apply what may happen or its price plan, this feature may be incorporated using EM algorithm method. So, we can review Cox's stress and graphic features by using AIPW schemes to incorporate data that contains incorrect data (or missing data) and more than once. By those parametric and semi-parametric ways, we can find which model is the best model to fit a data for this study.

### **Acknowledgement**

It is with immense pleasure that, I prepared this project report first and foremost my sincere thanks and appreciation to STAT654 course (Fall 2017) instructor Dr. Sanjel Deepak, Professor of Statistics, Department of Mathematics and Statistics, Minnesota state university, Mankato, USA for his tremendous assistance and valuable guidance.

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## Appendix:

```
options nodate nonumber ps=2000 ls=100;
data pbc;
infile 'E:\STAT654p\pbc.dat.txt';
    input id futime status drug age sex ascites hepato spiders edema
           bili chol albumin copper alk_phos sgot trig platelet
           protime stage;
    age = age/365.25;
if _n_ > 312 then delete;
if status=1 then status=0;
run;

PROC PRINT DATA=pbc;
RUN;

proc lifetest data=pbc atrisk outs=outpbc;
time futime*status(0);
run;

proc lifetest data=pbc atrisk plots=survival(cb) outs=outpbc;
time futime*status(0);
run;

proc lifetest data=pbc atrisk nelson;
time futime*status(0);
run;

proc lifetest data=pbc atrisk nelson;
time futime*status(0);
run;

proc lifetest data=pbc atrisk plots=survival(atrisk cb) outs=outpbc;
strata sex;
time futime*status(0);
run;
```

```

proc lifetest data=pbcc atrisk plots=hazard(bw=200) outs=outpbcc;
strata bili(15,18.5,25,30,40);
time futime*status(0);
run;

proc phreg data = pbcc;
class drug sex ascites hepato spiders edema;
model futime*status(0) =drug age sex ascites hepato spiders edema bili chol
albumin copper alk_phos sgot trig platelet protime stage;
run;

proc phreg data=pbcc plots=survival;
class drug sex ascites hepato spiders edema;
model futime*status(0) =drug age sex ascites hepato spiders edema bili chol
albumin copper alk_phos sgot trig platelet protime stage;
run;

```