Analysis of Mortality in a Small Sample of Older Adults

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Abstract

This paper presents an analysis of mortality in a sample of 441 adults aged 55 to 85 at baseline, who were observed for eight years.

Subjects living in London, Ontario, Canada, were recruited in 1987 using an approach designed to include at least 35 individuals in each of the six quinquennial age groups from 55 to 85, with roughly equal numbers of males and females. Considerable information was collected on each subject. Demographic and lifestyle data were obtained using a questionnaire, and a variety of physical measurements were taken in a laboratory.

We use the well-known proportional hazards model to assess the impact of these variables on mortality and to quantify mortality rates as a function of age and sex. The variability of the latter results is examined using simulation. Since the sample size is very small by actuarial standards, we are careful about the quantitative conclusions that are made.

1 Introduction

In attempting to quantify mortality levels and patterns at advanced ages, one invariably faces the challenge of small data sets. The older the age range that one considers, the smaller are the available data sets. Actuaries have traditionally had the luxury of rather large amounts of data for mortality analyses due to the large numbers of policies sold by life insurers. When working with a smaller data set, it becomes very important to choose analysis methods that make the most of the data available.

It is worth noting that whether a data set is small or large is relative to the problem the analyst faces, or to the question he or she must answer. It generally requires more data to decide whether a mortality rate is 0.010 or 0.011 than it does to decide whether or not a new drug leads to significantly longer lifetimes. For this reason, clinical trials typically involve many fewer subjects than life insurance mortality studies. So, in selecting advanced age mortality data, it is important to keep in mind the question(s) to be answered.

It is also important to recognize that "the data" is not the only data one will use in the analysis, particularly in an analysis of mortality. Actuaries have a very good understanding of how human mortality "should" behave. This is data, and to the extent that it is used in an analysis, it compensates for the size of the data set. Most actuaries agree that the progression of mortality rates with age should be smooth. When smoothing techniques are used, the variances of the estimators of mortality rates are reduced, as is the case when the size of the data set is increased.

In this paper, we discuss an analysis of the mortality of a sample of 441 older adults living in London, Ontario, Canada. The data were not collected for the purpose of studying mortality. Rather, the study was initiated by the Centre for Activity and Ageing at the University of Western Ontario for the purpose of analyzing age-related changes in a variety of physical variables and their impact on functional independence. As one might expect, however, some (66) of the subjects died during the initial eight-year follow-up period. Thus, the data provide a unique opportunity to study the mortality of this older group and how mortality is affected by the physical and demographic variables that were measured.

In Section 2 of this paper, we describe the data set. We indicate the variables that were captured for our analysis as well as our efforts to make the data more suitable for an analysis of mortality.

In Section 3, we determine which variables have a significant impact on mortality. This is done using the well-known proportional hazards regression model. We find the variables having the greatest impact are sex and vo2max. The latter is a measure of cardiorespiratory fitness.

Our efforts to quantify overall mortality are discussed in Section 4. We first present some crude mortality rates that give a rough indication of the variation in mortality by age and sex. We then construct a semi-parametric model. We again make the proportional hazards assumption to reflect the impact of sex, and we use a kernel estimation approach to obtain a force of mortality that is a smooth function of age. The variability of the resulting estimators of mortality rates is assessed by using simulation.

Some concluding remarks are made in Section 5.

2 The Data

The data we analyze are from a study initiated in 1987 by researchers in the Centre for Activity and Ageing (the Centre) at the University of Western Ontario. The goals were to examine how physical activity varies with age and how physical activity relates to vigor and independence.

The researchers sought a stratified sample of 420 subjects between ages 55 and 85, with 35 subjects in each of 12 categories based on sex and quinquennial age groups. The sample was drawn from the non-institutionalized population of London (total 1987 population 280,000). The sample selection methods are described by Koval et al. (1992). Ultimately, 441 subjects agreed to go to the Centre for a 3-hour session. This involved completion of a questionaire about their physical activity habits, a medical exam and medical history, a variety of physical measurements, a self-paced walking test, and a treadmill test. The breakdown of the 441 participants by age group and sex is given in Table 1.

Although not all 441 subjects were found to be healthy enough to submit to the physical tests, we can view this group as somewhat "select," since they are non-institutionalized, were capable of getting to the Centre, and believed they were healthy enough to participate in the study. We therefore expect this group of lives to have better mortality than the general population.

A great deal of information was obtained about each subject. For our analysis, we captured a number of variables that we thought might be relevant in a study of mortality. The demographic/socioeconomic variables we considered were marital status, level of formal education, occupational status, an indication of how well money takes care of the individual's needs, the individual's perception of his/her financial situation compared with others, life satisfaction, and happiness. The health/physical variables we considered were smoking status, self-health rating, anxiety and depression level, indicators of whether or not the individual has angina, hypertension, or diabetes, shoulder flexibility, hip flexibility, grip strength, plantar flexion (ankle) strength, skin-fold thickness, body mass index, vo2max (a measure of cardiorespiratory fitness), and physical activity level.

As mentioned earlier, the data used in this analysis were not collected for the purpose of studying mortality. For this reason, the mortality information was less than perfect. At the time of the 8-year follow-up, subjects were contacted for the purpose of collecting data on changes in variables measured at baseline. At that time, it was determined that 66 of the 441 individuals had died.

The date of death was provided for some subjects. For others, the person whom the Centre contacted either did not know the date of death or did not provide it. In an effort to obtain dates of all known deaths, death certificate searches were initiated. We were able to determine the dates of 56 out the 66 deaths. For the other 10 deaths, we concluded that the death was registered outside of the province of Ontario, or was registered under a name that differed somewhat from the name on file, or was not registered at all.

In our analysis, we assumed that the 10 subjects for whom the date of death is unknown died exactly 4 years after the start of the study. Thus, we have a maximum error of 4 years. We could have made no assumption about the time of death and treated these subjects as "interval censored" observations. However, we decided that this would complicate the analysis considerably and likely would not materially improve the quality of our analysis.

3 Factors Affecting Mortality

Before proceeding with our analysis of mortality, we did some preliminary investigation to better understand the sample population. Much of this involved examining tabulations of subject counts corresponding to different values of the variables mentioned in the previous section. Since many of these variables did not appear to affect mortality, we do not show the tabulations here.

The impact of various factors (explanatory variables) that might affect mortality was then examined using the well-known proportional hazards model. Under this model, it is assumed that the forces of mortality, also known as the hazard functions, are proportional for different values of an explanatory variable. More specifically, the force of mortality for an individual with explanatory variable values given by the vector $\boldsymbol{Z}$ is assumed to be

$$\mu(x|\boldsymbol{Z}) = \mu_0(x)\exp(\boldsymbol{\beta}'\boldsymbol{Z}),$$

where $\mu_0(x)$ is the "baseline" force of mortality to which all force of mortality functions are proportional, and $\boldsymbol{\beta}$ is a vector of parameters that must be estimated. If a given component of the $\boldsymbol{\beta}$ estimate does not differ significantly from 0, then the corresponding component of $\boldsymbol{Z}$ is not important in estimating the force of mortality.

We should note that the ability of this method to detect mortality differences associated with the different values of an explanatory variable is influenced by the extent to which the forces of mortality are proportional for the different values of the variable. Mortality differences involving, say, forces that cross each other may go undetected. However, such differences would seem less plausible than proportional forces.

The $\boldsymbol{\beta}$ parameters can be estimated by maximizing the partial likelihood function. When the ages at death $x_1, x_2, \ldots, x_D$ are distinct, this function is given by

$$L(\boldsymbol{\beta}) = \prod_{i=1}^{D} \frac{\exp(\boldsymbol{\beta}'\boldsymbol{Z}_{(i)})}{\sum_{j\in R(x_i)}\exp(\boldsymbol{\beta}'\boldsymbol{Z}_j)},$$

where $\boldsymbol{Z}_j$ is the $\boldsymbol{Z}$ vector for subject j, $R(x_i)$ is the set of subjects exposed to the risk of death at age x_i, and $\boldsymbol{Z}_{(i)}$ is the $\boldsymbol{Z}$ vector for the subject who actually died at age x_i. The partial likelihood represents the product over all ages at death of the conditional probability that the individual who died at a particular age at death is the one to die given that a death occurs and given the set of subjects at risk at this age. A desirable feature of the partial likelihood is that it does not involve the baseline force of mortality. Thus, inferences about $\boldsymbol{\beta}$ can be made without having to estimate the baseline force. In the event that the ages at death are not distinct, an adjustment to the above partial likelihood expression is required (see Klein and Moeschberger, 1997).

The proportional hazards model was fit multiple times, with each fit including one explanatory variable. The variables considered were those mentioned in Section 2 and a variable indicating the sex of the subject. We found that the sex variable was the most significant. When this was the variable included in the model, the p-value for a test of the hypothesis that $\boldsymbol{\beta}=\mathbf{0}$ was smallest. We then fit the model multiple times with each fit including the sex variable along with one of the other variables.

We found that vo2max was the most significant among those remaining. This is a variable that measures maximal oxygen uptake expressed in milliliters per minute per kilogram of body mass. It is widely considered an appropriate measure of cardiorespiratory fitness. We observe that vo2max decreases with age for both males and females. The value for males is higher at the younger ages, but decreases more steeply. (See Figure 1.) The fact that cardiorespiratory fitness decreases with age was confirmed by Stathokostas et al. (1999), who used the same study of London residents with the addition of 10-year follow-up measurements of vo2max. Over the 10 years, vo2max decreased by an average of 17.4 percent for males and 8.6 percent for females.

Fitting the proportional hazards model again with sex, vo2max, and one other variable, we found that none of the other variables were significant. Below are the results of fitting the model with the sex and vo2max variables.

Variable	$\hat{\boldsymbol{\beta}}$	$\exp(\hat{\boldsymbol{\beta}})$	Standard Error of $\hat{\boldsymbol{\beta}}$	p-value
Sex (1=M, 0=F)	1.252	3.499	0.3368	0.00020
Vo2max	-0.126	0.881	0.0382	0.00093

These results indicate that the force of mortality for males is 3.499 times that for females, and the force of morality decreases by a factor of 0.881 with each unit increase in vo2max. Careful interpretation of these numbers is required. Firstly, the proportionality factor for sex seems quite large. This is because males have larger values of vo2max than females. Hence, this large factor is offset to some extent by the proportionality factor for vo2max. Secondly, the latter factor is quite dramatic (small) because vo2max is correlated with age. Therefore, this factor reflects to some extent the impact of other age-related factors. We can therefore accept the conclusion that sex and vo2max are related to mortality, but we recognize that the above $\boldsymbol{\beta}$ estimates are not very useful.

As stated above, the validity of this analysis depends on the reasonableness of the proportional hazards assumption. To check this assumption for sex and vo2max, we plotted estimates of the cumulative (integrated) force of mortality obtained using the Nelson-Aalen (N-A) estimator. That is, if

$$M(x) = \int_0^x \mu(y)dy,$$

then the N-A estimate of $M(x)$ is

$$\hat{M}(x) = \sum_{x_i \le x} \frac{d_i}{Y_i},$$

where d_i is the number of deaths at age x_i, and Y_i is the number of individuals exposed to the risk of death at age x_i. If the forces of mortality are proportional for males and females, then the cumulative forces must also be proportional. Figure 2 shows the N-A estimates (along with approximate 95 percent confidence interval) plotted separately for males and females on the same graph. By examining this graph we cannot conclude that there is a serious departure from proportionality. Figure 3 shows the N-A estimates plotted separately for those with vo2max less than 20 and those with vo2max greater than 20. Again, the proportional hazards assumption seems reasonable.

Some further remarks about these results should be made. We recognize that, while sex and vo2max were the only variables found to be significant, this does not mean that they are the only ones that affect mortality. It simply means that our data provide insufficient evidence that other variables affect mortality. This is not surprising, as our data set is quite small. In particular, a number of the variables considered reflect the health of the individual. It is very interesting that, of all of these variables, the one that had the greatest effect on mortality was vo2max. This suggests that there may be value in studying how cardiorespiratory fitness is related to other health variables and the extent to which it can be controlled. Other studies have also found a relationship between cardiorespiratory fitness and mortality (see, for example, Blair et al., 1989).

For many years, actuaries have recognized smoking as an important predictor of mortality. However, we did not find smoking status to be significant in our analysis. This may be partly because only a small proportion of subjects were smokers and partly because we considered only smoking status at the start of the study. Some subjects may have already quit smoking due to poor health. Had we considered the smoking histories of the subjects, our results may have been different.

Finally, we have identified vo2max as a variable that affects mortality. Our model includes the value of this variable at the beginning of the study. However, for each individual, this variable changes over time. Thus, to appropriately model the impact of cardiorespiratory fitness on mortality, it should be treated as a "time-dependent" variable. We are unable to do this because we have its value at just one point in time for each subject.

4 Overall Mortality

To obtain a rough idea of the overall mortality of this sample of lives, we determined the exposure and number of deaths by sex and quinquennial age group. The exposure was calculated as the total time lived within the age group by all subjects of a given sex. A crude mortality rate was then calculated as the number of deaths divided by the exposure. Note that, if one assumes that the force of mortality is constant within 5-year age groups, this crude mortality rate is the maximum likelihood estimate of the force of mortality. The standard error of the corresponding estimator was estimated as

$$\frac{\sqrt{\text{number of deaths}}}{\text{exposure}},$$

an approximation that is commonly used. The results are shown in Table 2. They indicate that mortality rates are generally higher for males than females and generally increase with age, as we expect.

Faced with the challenge of more precisely quantifying overall mortality as a function of age and sex for a sample of 441 older adults, a common actuarial approach would be the following:

- Determine the overall ratio of actual to expected number of deaths, where the latter is based on a mortality table constructed from a population believed to have similar characteristics to that of the sample.
- Multiply this ratio by the each mortality rate in the table.

This method is very effective, though somewhat restrictive. It does not allow one to observe any differences in the age-related behavior of mortality rates between the sample and the mortality table. One could argue that a sample of 441 individuals does not provide credible information about this behavior. However, there are methods that allow one to explore this. We pursue these below.

We use the following proportional hazards model.

$$\mu(x|Z) = \mu_0(x)\exp(\beta Z),$$

where $\mu_0(x)$ is the baseline force of mortality, Z indicates the sex of the individual, and β is a scalar parameter which determines the male versus female proportionality factor. We assume the male and female forces are proportional because the number of female deaths is quite small (23), and, as indicated in Section 3, Figure 2 suggests that the proportionality assumption is reasonable. If we had evidence against this assumption, it would be possible to assume that the proportionality factor is a linear function (or some other function) of age. This would introduce one additional parameter, but still allow us to avoid modeling male and female mortality separately.

The parameter β was estimated by maximizing the partial likelihood. We obtained the estimate $\hat{\beta} = 0.6777$. Therefore the factor one must multiply by the female force of mortality to obtain the male force of mortality is estimated as $\exp(\hat{\beta}) = 1.969$. Notice that this number is much smaller than the 3.499 that was obtained in Section 3 when vo2max was also included in the model.

The baseline force of mortality was estimated by first estimating the cumulative (integrated) force using the Breslow estimator, which is a generalization of the Nelson-Aalen estimator. We use the Breslow estimator instead of the Nelson-Aalen estimator because the former allows us to estimate the baseline hazard function using data for males and females combined, but appropriately reflecting the difference in mortality between males and females. If

$$M_0(x) = \int_0^x \mu_0(y)dy,$$

then our estimate of $M_0(x)$ is

$$\hat{M}_0(x) = \sum_{x_i \le x} \frac{d_i}{\sum_{j \in R(x_i)} \exp(\hat{\beta} Z)}.$$

We next estimated the force itself by smoothing the increments of $\hat{M}_0(x)$

using a kernel function approach. That is,

$$\hat{\mu}_0(x) = \frac{1}{b}\sum_{x_i} K\left(\frac{x - x_i}{b}\right)[\hat{M}_0(x_i) - \hat{M}_0(x_{i-1})],$$

where b is the bandwidth, which controls the degree of smoothness, and $K(x)$ is the kernel function. We chose a bandwidth $b = 8$, which seemed to produce adequate smoothness without substantially distorting the shape of the resulting force of mortality.[1] A variety of kernel functions could be used. We chose the popular Epanechnikov kernel

$$K(x) = \begin{cases} \frac{3}{4}(1 - x^2), & -1 \le x \le 1 \\ 0, & \text{otherwise} \end{cases}.$$

Recognizing that the above kernel estimator will underestimate the force when x is within b of the youngest and oldest ages at which subjects are under observation, we made standard adjustments to the kernel function at these ages (see Klein and Moeschberger, 1997).

An estimate of the variance of $\hat{\mu}_0(x)$ can be obtained using

$$\widehat{Var}[\hat{\mu}_0(x)] = \frac{1}{b^2}\sum_{x_i} K\left(\frac{x - x_i}{b}\right)^2 [\hat{M}_0(x_i) - \hat{M}_0(x_{i-1})],$$

Then approximate 95 percent pointwise confidence intervals are given by

$$\hat{\mu}_0(x) \pm 1.96\sqrt{\widehat{Var}[\hat{\mu}_0(x)]}.$$

The natural logarithm of the force of mortality estimates along with the approximate 95 percent confidence limits are shown in Figure 4. The confidence intervals are quite wide at the extreme ages due the very small exposure at these ages.

Since actuaries typically work with mortality rates rather than forces of mortality, we used the estimated baseline force and proportionality factor to obtain estimated mortality rates for males and females. Now

$$q_x^Z = 1 - \exp\left(-\int_0^1 \mu(x + t|Z)dt\right).$$

[1] As the bandwidth increases, the variance of the kernel function estimator decreases, but its bias increases. It has therefore been suggested that one can obtain the "optimal" bandwidth by choosing b to minimize the mean squared error. However, this approach ignores any prior opinion one may have about the appropriate degree of smoothness.

Since we have used a kernel function estimator to estimate $\mu_0(x)$, the integral used in estimating q_x^Z must be computed numerically. An alternative numerical approach recognizes that, for large n,

$$q_x^Z \approx 1 - \prod_{i=1}^{n} \left(1 - \mu\left(x + \frac{i-1/2}{n}\Big|Z\right)\frac{1}{n}\right).$$

Therefore, we used

$$\hat{q}_x^Z = 1 - \prod_{i=1}^{100} \left(1 - \hat{\mu}\left(x + \frac{i-1/2}{100}\Big|Z\right)\frac{1}{100}\right).$$

These estimates are shown in Table 3. It is interesting to note that, except at the very young ages and the very old ages, where our confidence in these estimates is extremely low, all of these mortality rate estimates lie between the first year select rates and the ultimate rates in the 1986-92 Canadian Institute of Actuaries Basic Tables (Aggregate, Age Nearest Birthday) developed by Panjer and Tan (1995). This comparison, shown for several ages in Table 4, reinforces our earlier statement that the sample under study is somewhat select.

While one can obtain an approximate variance expression for $\hat{q}_x^Z$, similar to that obtained for $\hat{\mu}_0(x)$, these expressions may only be accurate in large samples. Furthermore, the normality assumption used to obtain confidence intervals may be inappropriate. To assess the variability of our estimators of the mortality rates, we used simulation instead. We assumed that our estimated forces of mortality for males and females were the true forces. Based on these forces, we simulated the mortality experience of our sample of 441 individuals over an 8 year period, thus producing simulated data of the same form as our actual data. We repeated this 100 times. For each of the 100 outcomes, we obtained mortality rate estimates in exactly the same manner as we did using the actual data. The standard deviation of the simulation estimates obtained for each age are included in Table 3. The results of these simulations are summarized in Figures 5 and 6.

Some explanation of the graphs in Figures 5 and 6 is required. Logarithms of mortality rates are plotted because the magnitude of the rates changes dramatically over the age range considered. Thus is easier to examine all ages on a single graph if logarithms are used. The solid line connects the logs of the mortality rate estimates obtained from the original data. The other information summarizes in the form of a Box plot the logs of the mortality rate estimates obtained from the simulation outcomes. The bottom of each box gives the first quartile of the simulation estimates. The top of each box gives the third quartile of the simulation estimates. The horizontal line within each box gives the median of the simulation estimates. The dashed lines extending out from each box (the "whiskers") reach the most extreme observations that are at most 1.5 times the inter-quartile range outside of the box. Any observations outside the whiskers are plotted as open circles. For both males and females, the box is not drawn at age 56. This is because the first quartile of the simulation estimates of the mortality rate obtained for this age is 0, the log of which is minus infinity. Since this cannot be included on the graph, the sides of the boxes have been omitted. The Box plots provide a visually appealing summary of the distribution of the simulation estimates.

The graphs in Figures 5 and 6 not only illustrate the variability of our estimates, but they also illustrate the bias. In particular, for ages greater than 80, a very high percentage of the simulation estimates lie above the estimate obtained using the actual data. Since the latter is the "true" value for the purpose of the simulation, our estimation procedure appears to overestimate the mortality in this age range. This is likely due to the fact that mortality rates are a convex function of age. The kernel function estimator therefore tends to overestimate. This bias can be viewed as acceptable if we believe that the smoothness it produces is appropriate.

5 Conclusions

In this paper, we have analyzed the mortality of a small sample of 441 older adults in London, Ontario, Canada. We examined the effect of a number of variables on mortality, and constructed a model for overall mortality by age and sex.

Using the proportional hazards model, we found that sex and cardiorespiratory fitness were significantly related to mortality. We again used the proportional hazards model along with a kernel estimator to obtain a semi-parametric model of mortality that describes how mortality varies by age and sex. We used simulation to assess the variability of our estimates of mortality rates. Using these methods, we are able to not only gain an understanding of overall mortality, but to quantify our uncertainty about the results.

An alternative to the semi-parametric model that we have used to represent overall mortality is a fully parametric model. That is, we could use a simple parametric function to reflect how mortality varies with age. We examined some simple two-parameter models (Gompertz, loglogistic, and Weibull), but found these to be unacceptable. In particular the fit at older ages was very poor. However, this approach could be explored further using models with three or more parameters.

The study of mortality at advanced ages is very challenging. The fairly rapid health deterioration that occurs, and eventually leads to death, is the result of a large number of interacting biological processes. It is impossible to observe all of the important variables related to these processes. However, if we can determine which of these variables have the greatest impact, we can better understand why some people age more rapidly than others, and we can better predict the mortality of older adults. Our study and other studies have found that cardiorespiratory fitness is an important predictor of mortality. Further research is needed to assess how these results extend to the very old ages (near 100), and to develop models that describe how cardiorespiratory fitness changes over time and how it and other important variables are related to mortality.

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A Tables

Table 1: Number of Subjects by Age Group and Sex

Age Group	Male	Female	Both Sexes
55-60	32	29	61
60-65	37	33	70
65-70	31	40	71
70-75	35	38	73
75-80	36	49	85
Over 80	38	43	81
Total	209	232	441

Table 2: Exposure, Deaths and Crude Mortality Rate

Males				
Age Group	Exposure	Deaths	Crude Mortality Rate	Standard Error
55-60	63.6000	0	0.0000	-
60-65	254.3831	2	0.0079	0.0056
65-70	241.1447	4	0.0166	0.0083
70-75	229.9300	3	0.0130	0.0075
75-80	257.8426	11	0.0427	0.0129
80-85	251.6496	5	0.0199	0.0089
85-90	177.4356	10	0.0564	0.0178
90-95	31.0007	8	0.2581	0.0912
Females				
Age Group	Exposure	Deaths	Crude Mortality Rate	Standard Error
55-60	60.7264	1	0.0165	0.0165
60-65	199.1000	0	0.0000	-
65-70	273.9637	1	0.0037	0.0037
70-75	287.3061	4	0.0139	0.0070
75-80	286.7377	2	0.0070	0.0049
80-85	311.2311	6	0.0193	0.0079
85-90	172.1858	8	0.0465	0.0164
90-95	28.5634	1	0.0350	0.0350

Table 3: Estimated Mortality Rates

	Males		Females	
Age	Mortality Rate	Standard Error	Mortality Rate	Standard Error
56	0.0014	0.0068	0.0007	0.0030
57	0.0029	0.0057	0.0015	0.0025
58	0.0038	0.0049	0.0019	0.0021
59	0.0050	0.0041	0.0025	0.0018
60	0.0066	0.0036	0.0034	0.0016
61	0.0080	0.0033	0.0041	0.0015
62	0.0088	0.0031	0.0045	0.0015
63	0.0094	0.0031	0.0048	0.0015
64	0.0097	0.0032	0.0050	0.0016
65	0.0099	0.0033	0.0051	0.0016
66	0.0105	0.0035	0.0053	0.0017
67	0.0113	0.0037	0.0057	0.0018
68	0.0127	0.0040	0.0064	0.0020
69	0.0149	0.0042	0.0076	0.0022
70	0.0171	0.0045	0.0087	0.0023
71	0.0191	0.0048	0.0097	0.0025
72	0.0206	0.0050	0.0105	0.0026
73	0.0219	0.0053	0.0112	0.0027
74	0.0234	0.0055	0.0120	0.0029
75	0.0252	0.0058	0.0129	0.0031
76	0.0268	0.0061	0.0137	0.0032
77	0.0281	0.0064	0.0144	0.0035
78	0.0295	0.0067	0.0151	0.0038
79	0.0318	0.0074	0.0163	0.0042
80	0.0340	0.0083	0.0174	0.0047
81	0.0362	0.0095	0.0186	0.0053
82	0.0385	0.0107	0.0197	0.0061
83	0.0419	0.0119	0.0215	0.0070
84	0.0497	0.0139	0.0256	0.0084
85	0.0635	0.0194	0.0328	0.0109
86	0.0818	0.0308	0.0424	0.0151
87	0.1026	0.0460	0.0535	0.0218
88	0.1270	0.0638	0.0666	0.0309
89	0.1564	0.0841	0.0827	0.0427
90	0.1917	0.1066	0.1024	0.0580
91	0.2347	0.1301	0.1269	0.0774
92	0.2880	0.1528	0.1583	0.1017

Table 4: Comparison of Mortality Rates

	Males			Females		
	Our	CIA	CIA	Our	CIA	CIA
Age	Estimate	Select	Ultimate	Estimate	Select	Ultimate
60	0.0066	0.00272	0.01052	0.0034	0.00201	0.00624
65	0.0099	0.00411	0.01749	0.0051	0.00314	0.01005
70	0.0171	0.00605	0.02861	0.0087	0.00503	0.01658
75	0.0252	0.00975	0.04612	0.0129	0.00843	0.02779
80	0.0340	0.01550	0.07331	0.0174	0.01425	0.04698
85	0.0635	-	0.11484	0.0328	-	0.07956
90	0.1917	-	0.17678	0.1024	-	0.13383

B Figures

Figure 1: Plots of Cardiorespiratory Fitness versus Age

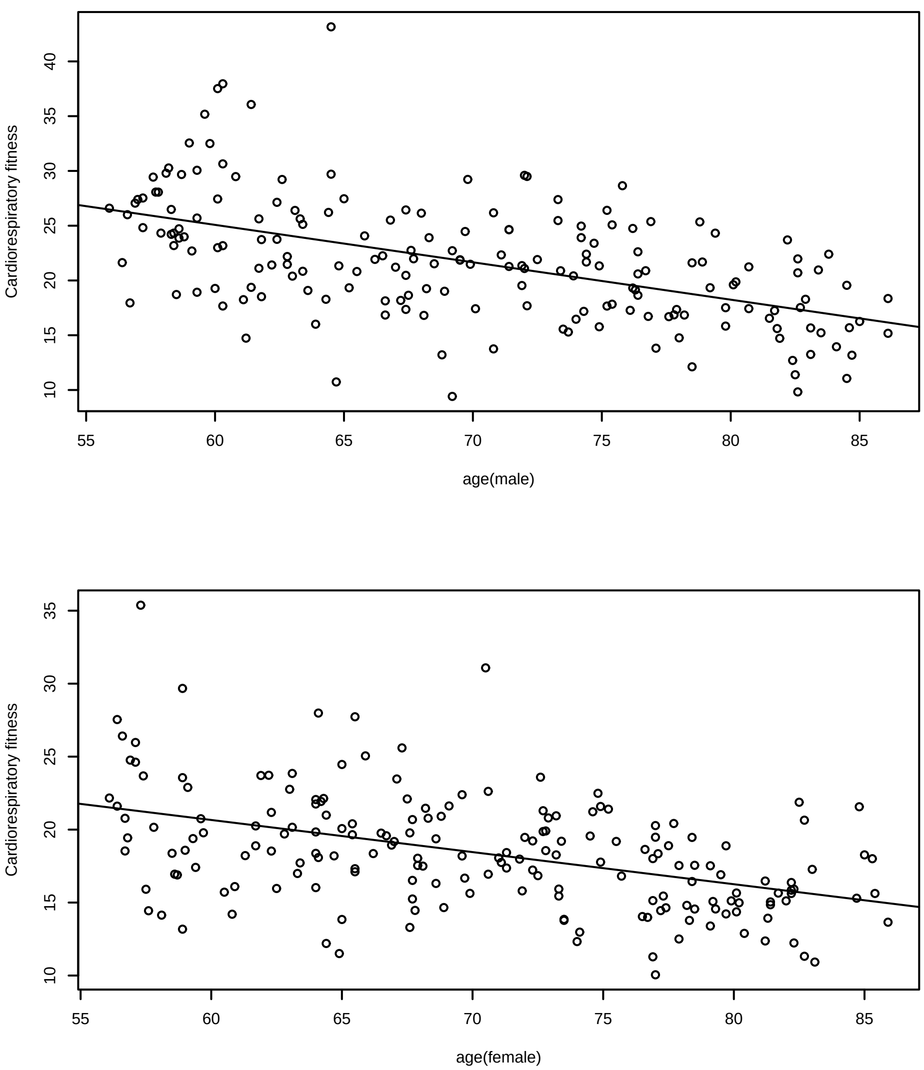


Figure 2: Cumulative Force of Mortality Estimates for Males and Females

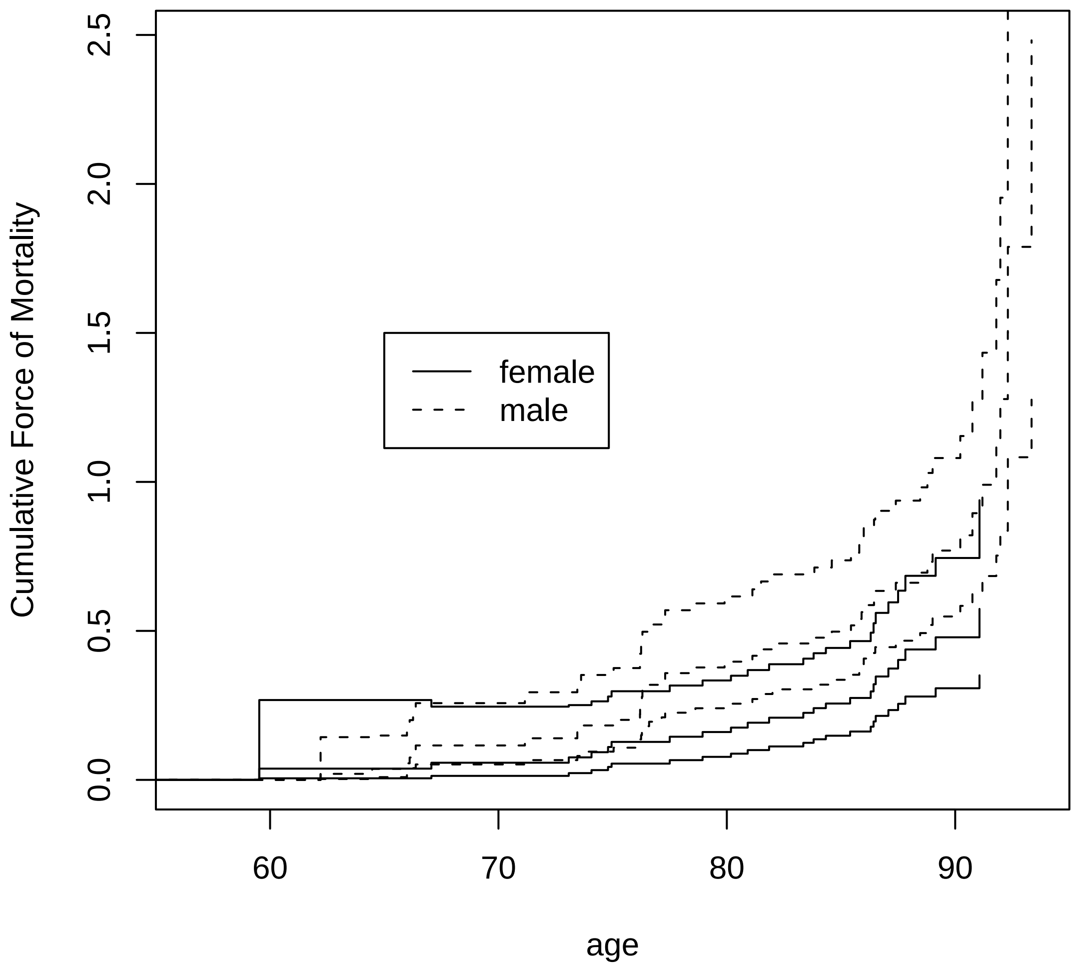


Figure 3: Cumulative Force of Mortality Estimates for Two Vo2max Groups

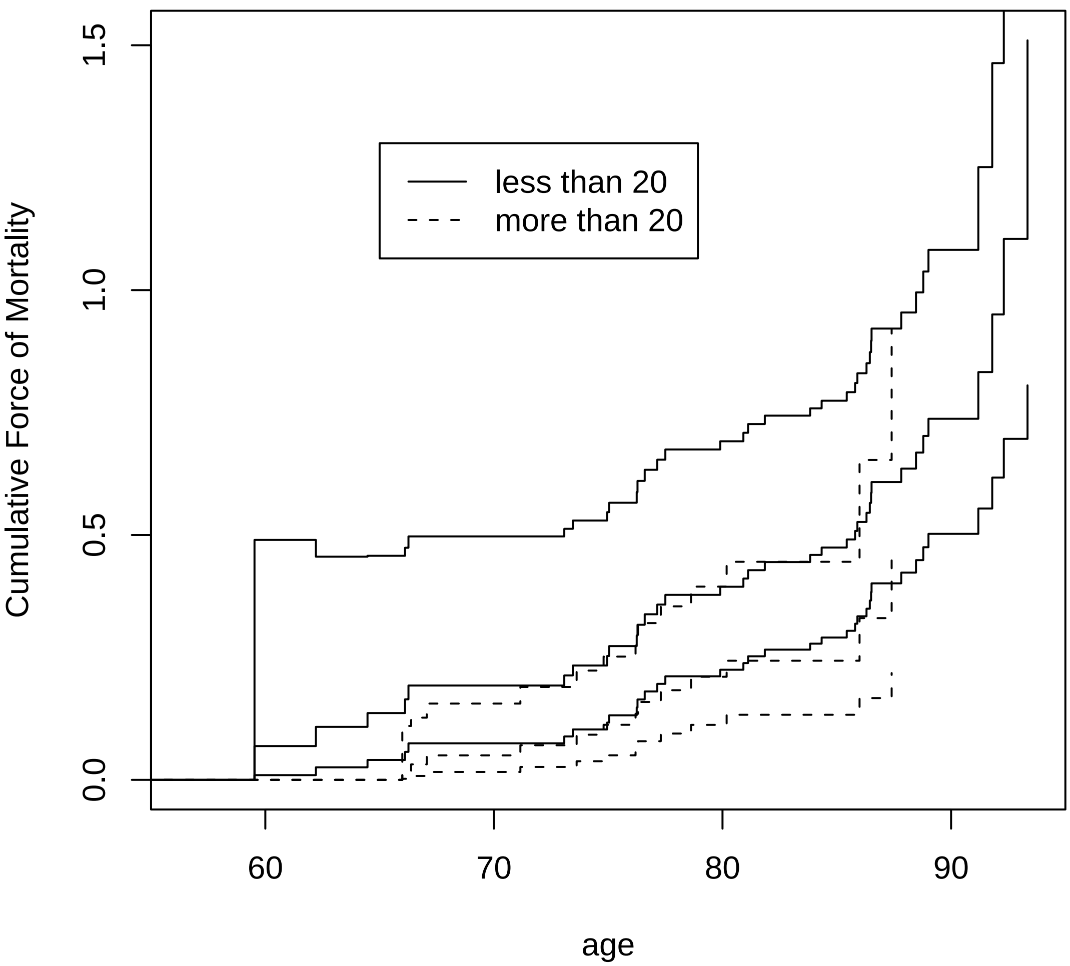
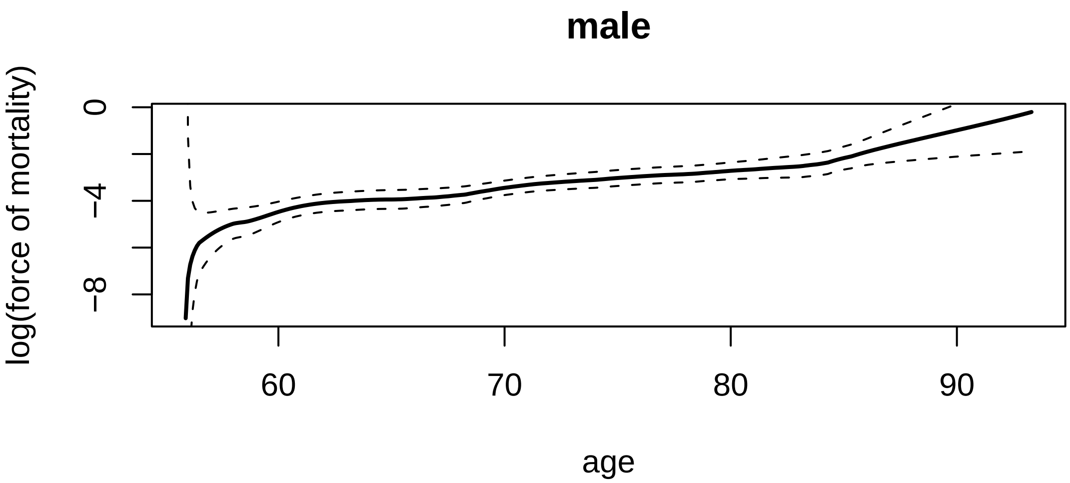


Figure 4: Log of Estimated Baseline Force of Mortality with Approximate 95 Percent Confidence Interval



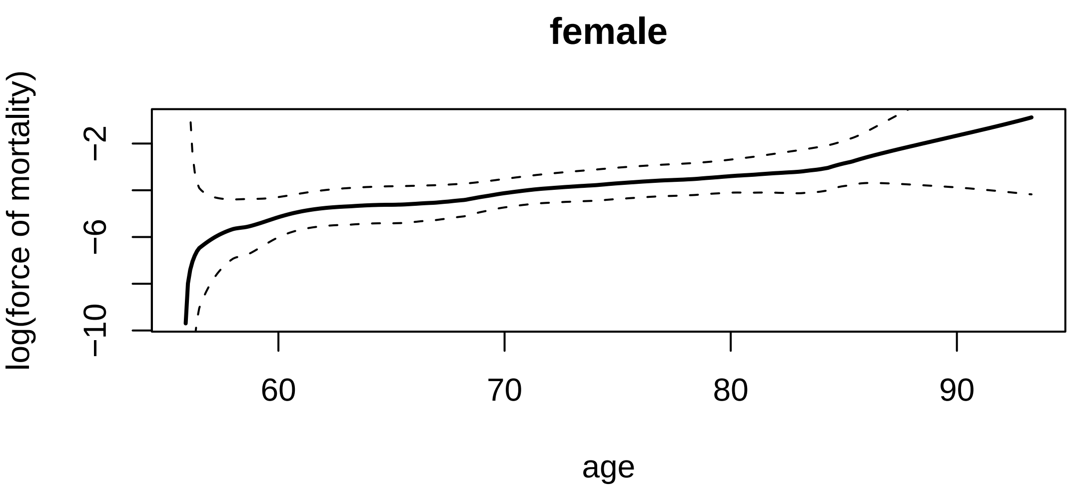


Figure 5: Log of Estimated Mortality Rates Obtained by Simulation (Males)

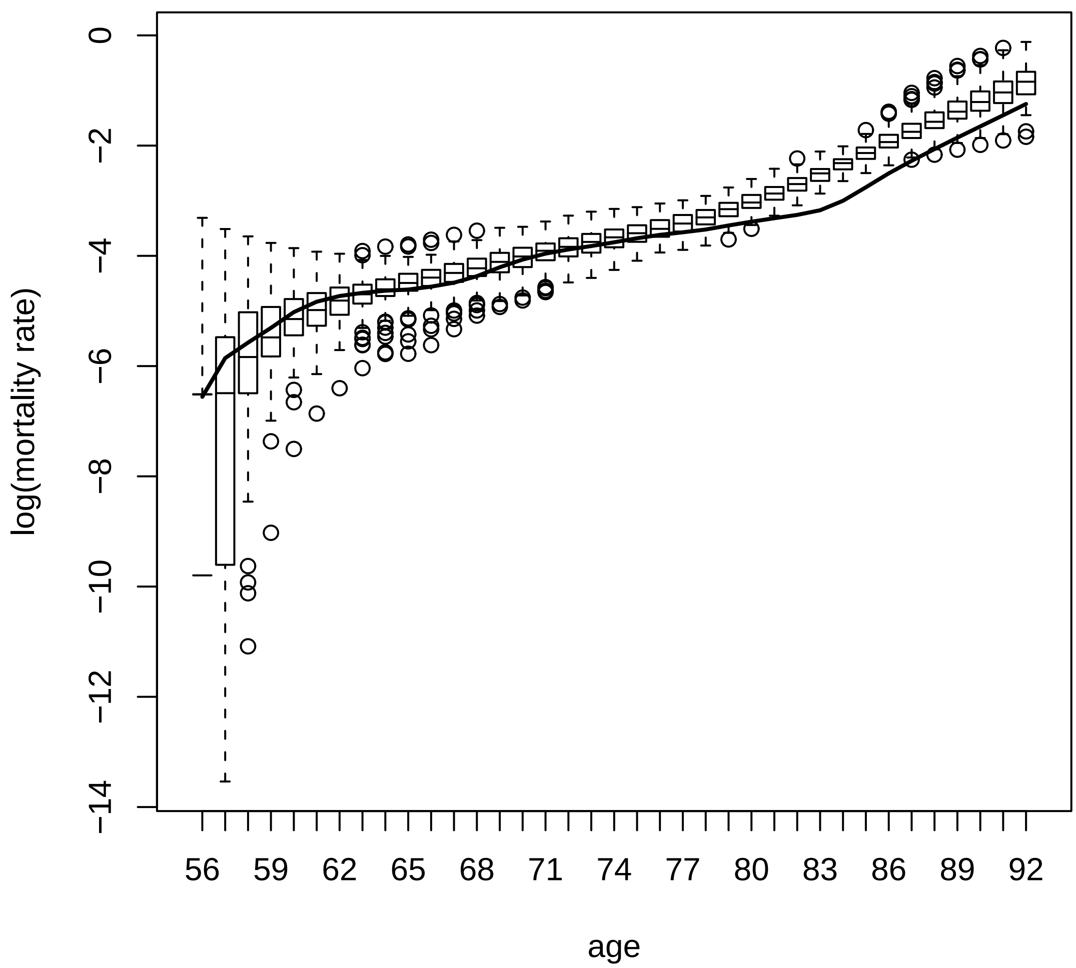


Figure 6: Log of Estimated Mortality Rates Obtained by Simulation (Females)