Survival Analysis of Post-Myocardial Infarction Patients

Research: Alvein, Parametric: Orr, Non-Parametric: Pham

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Abstract

Background: The rates of myocardial infarction is becoming an increasing common occurrence in the United States. Rapid development of medical technology and knowledge have led to an decline in myocardial infarction fatalities[6]. However, there is much to be learned regarding the survival probabilities of patients following an infarction episode.Some studies have already examined the effects of externalities on the survival rates of these patients[8].

Objective: Our goal is to provide detailed survival statistics of patients during a post-myocardial infarction time period with specific concern addressed to age, ventricular activity, and physiological cardiac state. Using these variables, we aim to provide succinct information on the current state of the dataset as well as provide robust predictors for the future estimates of survival for future patients.

We aim to fit non-parametric (Kaplan-Meier) and parameters curves to describe the data as well as choose a regression model to be used for predictive survivability.

Methods: Data from 130 post-myocardial infarction patients measure the time in months until death in a one year monitoring period of follow-up. We use a combination of non-parametric (Kaplan-Meier) and parametric methods (Weibull, Log-Normal, Log-Logistic, Cox PH) to determine estimates of survival among gender and physiological cardiac state (contraction depth, muscular activity, anatomical status). We fit multiple distributions over the dataset to provide current-state information of the patient dataset. Then, we regress multiple models and use combination of Akaike Information (AIC) statistics, logistic ratio tests, and residual analysis to determine model adequacy.

Results: Non-parametric Kaplan-Meier curve shows a median survival time of ~30 months for all age groups with the exception of pericardial effusion presence. Patients with pericardial effusion have a slightly lower . We choose a Weibull regression fit (tentative) for predictive model as we have favorable AIC, ratio, and residual indicators out of all of our model.

Conclusion: Thus, for predictive model we found the Weibull regression fit to be the most ideal candidate for modeling survivability for patient groups. Additionally, when examining the survival times for the Kaplan-Meier step curve, we see that the younger age groups do survive as well as their older counterparts. Given our limited sample size for that population, we recommend continued studies into external effects of the post-myocardial episode survival.

Introduction

Heart disease has become the leading cause of US deaths among all racial and ethnic groups[2,7]. In 2009 cardiovascular disease represented nearly 64% of all cardiac related deaths[4]. These myocardial infarction – commonly known as heart attacks - are becoming largely common among all U.S. demographic populations. As such, researchers are looking to understand the underlying causes of these episodes. Specifically, increases in cardiovascular disease (CVD) cases have been largely attributed to many risk factors such as high levels of low-density lipoproteins (LPL), high blood pressure, and smoking[2].

These variables are often the results of lifestyle choices and effects of poverty. The prevalence of the disease has closely been followed a large body of conducted researchers aiming to reduce either the number of these cases or reduce the mortality of the specific myocardial infarction rates. Between 1980 and 2002, mortality rates saw a decrease of approximately 49%[15]. Decreases in mortality was common through the world better medical intervention techniques and increase awareness of healthier lifestyle choices became more prevalent[5].

Unsurprisingly, as more patients survive CVD related infarction episodes, more detail has been paid to understand the survivability the time period following an episode. Wall motion score (a measure of heart contractility during cycling) was significantly higher in those that survived versus those that died[7]. We hope to examine several factors that determine survivability among these patients. In addition to wall motion score, we hope to stratify and understand the relationships between time to event (death) measurements compared to general heart health and age. Our goal is to describe the survivability of our dataset and provide a model to predict the factors that determine survivability in the one-year period following a myocardial infarction episode.

Dataset

Our data was obtained our data set from Kaggle via the Reed Institute. The data set contains 133 total patient observations across 8 variables: status at the end of the survival period, age, presence of pericardial effusion, fractional shortening, EPSS, wall motion score, wall motion index, and alive at the end of one year. Three patient survival times were not given; thus, we elected to remove those values to develop the most accurate portrayal of survival times.

Since the time of myocardial infarction varies (depending if a patient joined the study prior to the start), some patients were followed for less than a year. This provides a clear censoring and truncation. We discuss the nature of censoring in the following section.

At this point, 40 points of data were missing from the total dataset. A random forest algorithm (see: missForest package) was employed to iteratively impute values. With this in mind, our predictive and summary models will have less than ideal accuracy.

We then classify continuous variables into groups for stratification.

Age is divided into two groups with 0 denoting younger than 63 years, 1 denoting older or equal to 63 years. Pericardial effusion is already grouped into binary values with 0 denoting the absence of fluid while 1 denotes the presence of the effusion. Wall motion score is divided into two groups: 0 denoting scores less than 14, 1 denoting scores greater than or equal to 14. Finally, we divided fractional shortening into two strata as well with 0 being lengths being less than 0.2 seconds and 1 being greater than or equal to 0.2 seconds.

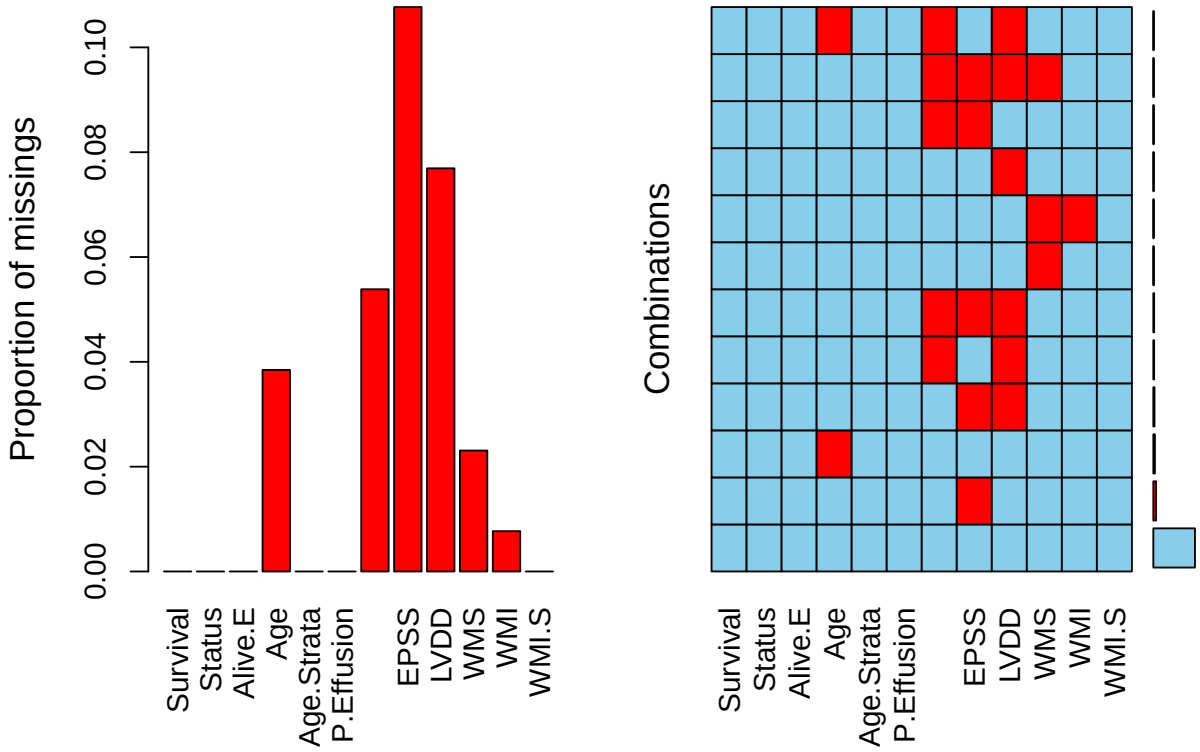
Table 1: Stratification Groupings

Indicator	Age	Effusion	WMS	FS
0	$<$ 63 Years	Fluid is absent	$<$ 11	$<$ 0.2
1	$=$ 63 Years	Fluid is present	$=$ 11	$=$ 0.2

The reader may find a summary of tables and original dataset in the appendix of this paper.

Imputation

In addition to the two rows that we removed, we further modified the dataset. The provided data contains 40 missing values that we chose to impute using the random forest algorithm methods in the missForest R package. The graphic below describes the number of missing values per variable:



We leverage the missForest package that uses algorithmic process used here uses a modified k-nearest neighbor (KNN) approach. Using a training data set, the routines of the algorithm predicts the missing values trained on the observed parts of the dataset[12]. The process checks each iteration for an acceptable amount of error. If an iteration produces an error that is smallest than that last iteration, then the algorithm continues to function. This progress stops when an error is larger than the previous iteration. Refer to Stekhoven, et. al 2012 for more detail.

We used the missFortune package to run up to 500 iterations. Each iteration was allotted 1000 trees for the random forest algorithmic approach.

Following imputation, we verify the imputation accuracy using the normalized root mean squared error as an indicator of accuracy (NRMSE)[8]. The general performance of our imputed dataset can be expressed by:

$$NRMSE = \sqrt{\frac{mean\left(\left(X^{true} - X^{imp}\right)^2\right)}{var\left(X^{true}\right)}}$$

Where X is a matrix of our dataset. Being a random forest iterative process, each imputed dataset will be different from each other. For our particular seed and iterations, we obtained a NRMSE value of 0.1442 - that is our inputted values have an estimate 14.42% deviation from estimated true accuracy.

The full imputed dataset may be found in the appendix of this paper. As well as references to the authors who created the algorithm.

Censoring

Our dataset has numerous censored valued - that is, valued that cannot be recorded due the constraint of the study design. In our data set, we are examining the survival after a heart attack, that is, the event of interest is death given that a patient has had already survived a heart attack (left truncation).

We have fixed start and end dates for when the data was collection. Some patients joined when the study began. Others joined later after the start date. Because of this, we cannot accurately determine how long a patient survived after our observation period is over. In addition, there are some patients that have been lost to follow up or may have died due to the onset of other unrelated factors. These data present themselves as being randomly right censored.

Methodology

Here, we briefly review the methodology and theory behind our analysis techniques for context.

Non-Parametric: Kaplan Meier

We use Kaplan-Meier (KM) survival estimators to model a step curve for the survival of our censored dataset. The KM estimator is an adjustment of an empirical survival function to reflect the presence of right-censored observations[14]. The estimator can be described in the following equation:

$$\hat{S}(t) = \prod_{y_{(i)} \leq t}^{k} p_i = \prod_{i=1}^{k} (\frac{n_i - d_i}{n_i})$$

Where n_i is the number alive before time y_i and d_i is the number of events during during that interval. In our case, y_i is the specific patient being observed, n_i is the number of patients alive at time y_i. With $k = 131$, our KM equation is:

$$\hat{S}(t) = \prod_{i=1}^{131} (\frac{n_i - d_i}{n_i})$$

We use this equation to estimate the survival at each time interval. We conduct this analysis for the whole data set and then choose to stratify on age, pericardial effusion presence, and wall motion score. We also include cumulative hazard estimators based on the KM fit. Additionally, as we stratify groups by covariates, we use the Mantel-Haenszel/log-rank test. The following equation is used to calculate the test statistic in order to compare two strata[14]:

$$Mantel - HaenszelStatistic = \frac{\sum_{i=1}^{k} (a_i - E_0(A_i))}{\sqrt{\sum_{i=1}^{k} Var_0(A_i)}}$$

Where,

$$E_0(A) = \frac{m_1 n_1}{n} \quad and \quad Var_0(A) = \frac{m_1(n - m_1)}{n - 1} * \frac{n_1}{n}(1 - \frac{n_1}{n})$$

We then use the Mantel-Haenzel statistics to perform a standard chi-square test to examine the differences between our strata.

Cumulative Hazard Estimator

We calculate the hazard of our Kaplan-Survivor function by observing standard cumulative hazard estimate (shown below):

$$\hat{H}(t) = -logS(t) = -log \prod_{y_{(i)} \leq t} \frac{d_i - n_i}{n_i}$$

Intuitively, the relationship of the observed hazard is the negative log of the survival function at each interval. We can clearly see a graphical relationship between our survival by examining our hazard plots in the results section. There was the possibility of using Nelson-Aalen's approximation for hazard, but we find that the computation is trivial.

Parametric Modeling of Survival Data

Another technique for characterizing the survival function is to assume a distributional model for the data. Compared with the Kaplan-Meier approach, this method has certain advantages that include a continuous survival curve and simplicity of estimation and prediction. If the selected model accurately describes the data, it may also lend insight into the underlying mechanism for the survival behavior. This method is only applicable if a distributional model can be identified that fits the survival data adequately.

For the post-myocardial infarction dataset, We fit three commonly employed distributional models to the survival data and evaluating goodness of fit of the three models. This is accomplished by comparing the modeled survival curves to the Kaplan-Meier curve and by comparing point estimates for each model.

The three models chosen for comparison are the well-known Weibull, Lognormal, and Loglogistic distributions.

The Weibull hazard function is given below, where λ and α are the scale and shape parameters. Weibull hazard is rising if$\alpha > 1$, constant if $\alpha = 1$, and declining if $\alpha < 1$.

$$h(t) = \lambda^{-1}(-log(1-p))^{1/\alpha}$$

The log-normal distribution can be defined relative to the standard normal distribution; a random variable Y may be said to have the log-normal distribution if for some random variable T that has standard normal distribution:

$$log(Y) = \alpha + \sigma T$$

The hazard function of the log-normal distribution increases with time from 0 until it reaches a maximum and then decreases, approaching 0 as time approaches infinity.

The log-logistic distribution can be defined relative to the standard logistic distribution; a random variable X may be said to have the log-logistic distribution if for some random variable S that has standard logistic distribution:

$$log(X) = \alpha + \sigma S$$

the hazard function of the log-logistic distribution decreases with time from ∞ if $\alpha < 1$, decreases from λ if $\alpha = 1$, and if $\alpha > 1$ resembles the log-normal distribution.

Semi-Parametric Modeling of Survival Data

Where fully parametric models offer flexibility and the efficient, relatively simple estimation of overall survival function parameters,semi-parametric models offer the advantage of being well-suited to the estimation of covariate effects. Semi-parametric models decompose risk into a baseline hazard component and a relative risk component that is dependent on the covariates.

The semi-parametric Cox proportional hazards model is employed here to explore the relationship between predictor variables and survival behavior.

The Cox PH hazard function is defined as follows:

$$h(t) = h_0(t) \times exp(b_1x_1 + b_2x_2 + ... + b_nx_n)$$

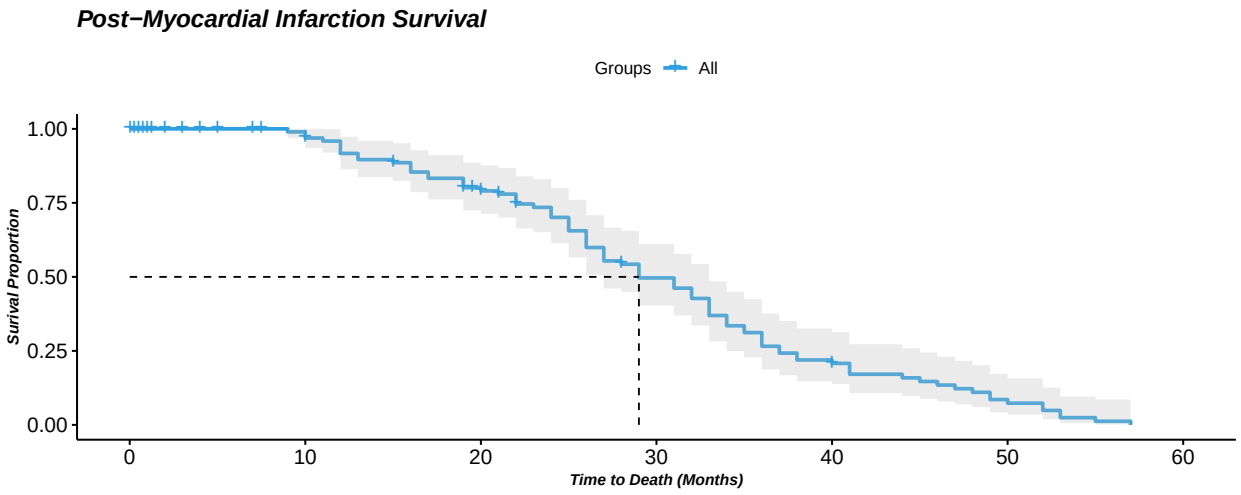
where t represents the survival time, $x_1, x_2, ..., x_n$ are the set of prognostic factors or covariates, and the coefficients $b_1, b_2, ..., b_n$ measure the effect of the covariates on survival time. The baseline hazard $h_0(t)$ corresponds to the value of the hazard if all covariates are equal to zero.

Use of the Cox PH model requires that the baseline hazard is not dependent on the covariates, and that the covariate terms do not depend on time - that is, that the slope coefficients are constant. Hazard functions stratified on covariate group may be used to assess the proportional hazard assumption. If the hazards functions for covariate groups cross over time, the proportionality assumption is not met and alternate analysis methods should be employed. One such method involves sub-setting the survival data and covariates based on hazard cross-over time. In this approach, a separate model is fit to each subset where it has been determined that the proportionality assumption holds. Alternately one may apply alternate modeling techniques that are suitable for time-varying effects, or simply investigate the impact of covariate by inspection of stratified Kaplan-Meier survival curves (Kim, 2000).

Results

Non-Parametric: Kaplan-Meier Survival Estimates

Kaplan-Meier estimates give us the following curve (full KM estimator table can be found in the appendix).

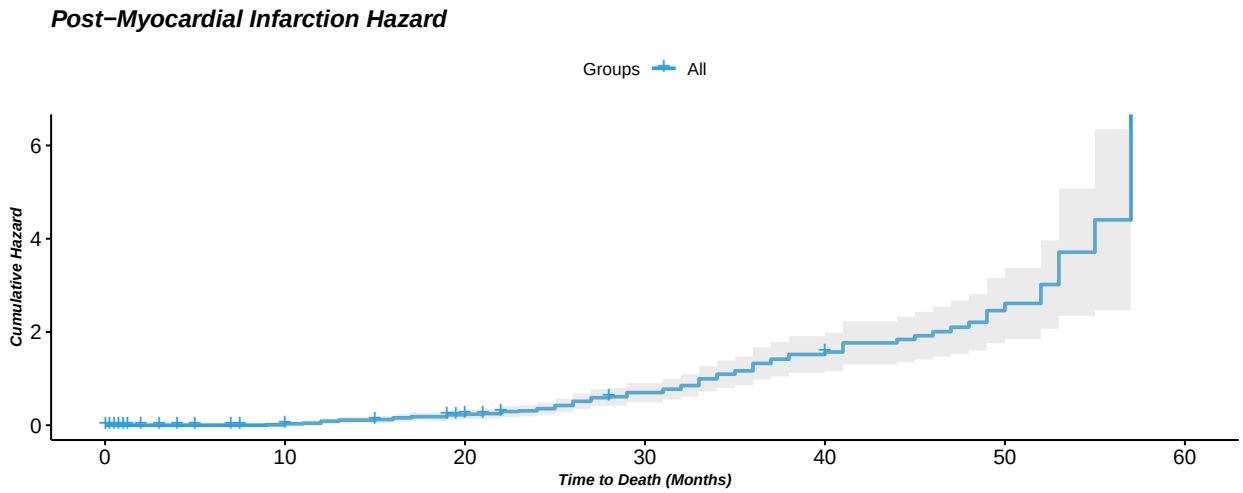


The Kaplan-Meier estimates for for all groups within our dataset is shown above. The curve follows a general pattern of decreasing survivability over time. With time spanning to a maximum of 57 months, we have a mean survival time of approximately 30.5 months. The median survival time is 29 months with 95% confidence limits between 27 and 33 months.

Table 2: Kaplan-Meier Estimates for All Groups

	Records	Events	Mean	Median	Median 0.95 LCL	Median 0.95 UCL
All Groups	130	88	30.53	29	27	33

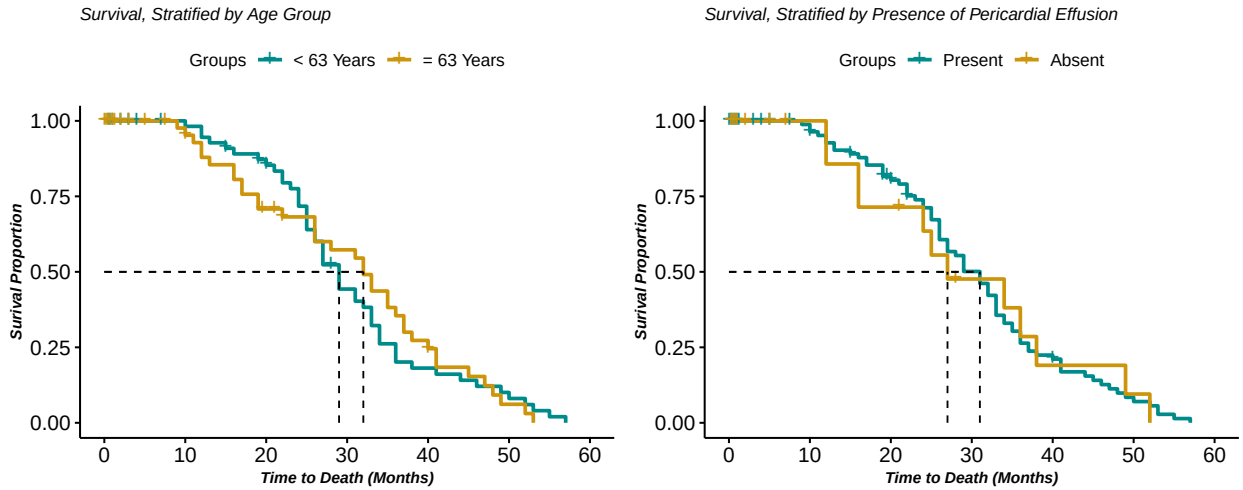
When testing for significant difference between strata groups we use the log-ran



To explore differences among groups, we stratify among age, pericardial effusion presence, wall motion score, and fractional shortening. We first begin exploring the effects of age and pericardial effusion presence:

Stratified by Age and Pericardial Effusion Presence

The results of a Kaplan-Meier estimate for age and pericardial effusion stratification can be seen below:



When stratified by age, we find a slight difference between the curves. The age group younger than 63 has a mean survival time of 30.47 months with a median survival time of 29 months. The older group - ages greater than 63 - has a similar mean survival time of 30.6 months and a slightly longer median survival time of 32 months. When comparing the presence of pericardial effusion, there are 106 cases where the effusion is absent, while 24 cases have the effusion present. The mean survival time when pericardial effusion is absent

Table 3: Kaplan-Meier Estimates Stratified by Age and Pericardial Effusion Presence

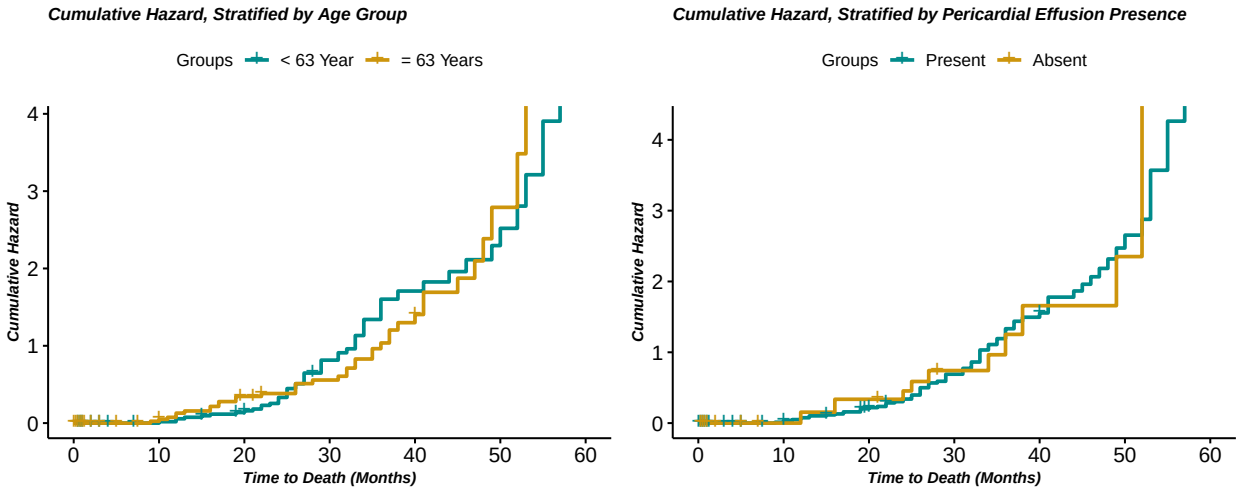
	Records	Events	Mean	Median	Median 0.95 LCL	Median 0.95 UCL
Age $<$ 63	66	51	30.47	29	26	33
Age $=$ 63	64	37	30.60	32	26	37
Absent	106	76	30.63	31	27	33
Present	24	12	29.94	27	24	NA

Table 4: Summary of Differences Between Strata

	N	Observed	Expected
Age $<$ 63	66	51	50.58084
Age 63	64	37	37.41916
Absent	106	76	76.42260
Present	24	12	11.57740

is 30.63 months with a median survival time of 31 months. For converse case, the mean survival time is 29.94 months while the median is lower at 27 months.

Log-rank tests between both stratification groups returns a p-value of 0.9 for both age strata and effusion strata. When testing at the 95% significance level, we do not have significant differences between groups.



For both groups, there does not seem to be a large departure from cumulative hazard. When stratifying by age, we see a slight increase in cumulative hazard of the younger group between 30 and 50 months. After that mark, the older group experiences a relative increase in cumulative hazard. When stratified by pericardial effusion presence, very little difference can be observed with any difference being the result of sample size differences.

Stratified by Wall Motion Score and fractional Shortening Length:

We then explore the effects of wall motion score and fractional shortening:

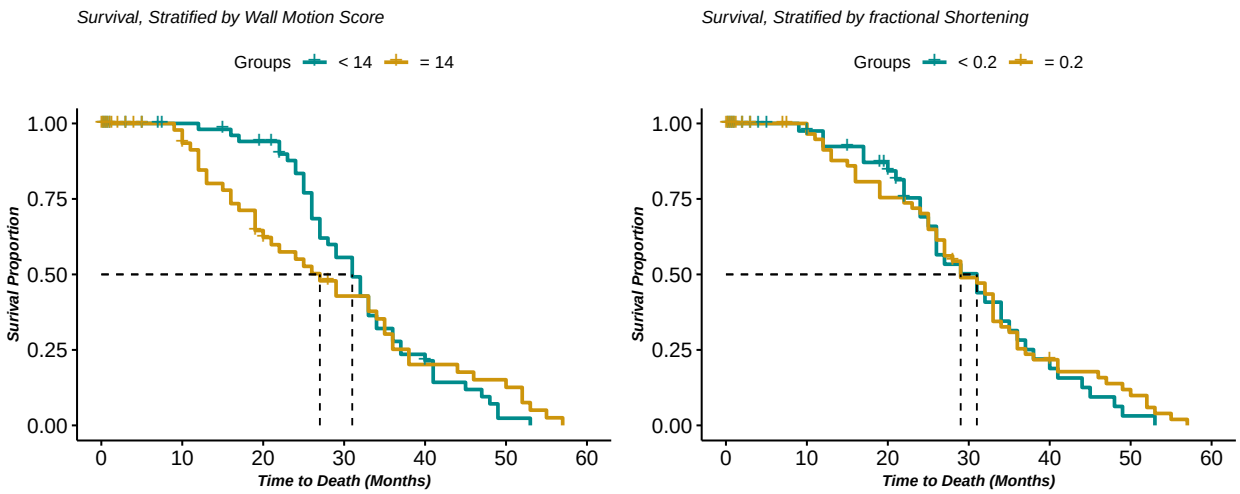


Table 5: Kaplan-Meier Estimates Stratified by Wall Motion Score and fractional Shortening

	Records	Events	Mean	Median	Median 0.95 LCL	Median 0.95 UCL
Score < 14	62	46	32.17	31	27	34
Score $= 14$	68	42	28.61	27	20	35
Length < 0.2	61	33	30.45	31	26	36
Length $= 0.2$	69	55	30.44	29	26	33

When stratified by wall motion score, we find a difference between the curves. Wall motion scores less

When stratified by fractional shortening length, both groups have a similar mean at approximately 30.4 r

Log-rank tests to test differences between wall motion score strata show p-value of 0.9 while the same

\begin{center}\includegraphics{markdown_files/figure-latex/km.haz2-1} \end{center}

Here, we see some minute differences between the hazard curves. When stratified by Wall Motion Score, w

When stratified by fractral shortening, the cumulative hazard curves are approximately similar with high

Parameter Estimation

The estimated distributional model curves are overlaid on the K-M curve for the post-myocardial infarcti

Table 6: Summary of Differences Between Strata

	N	Observed	Expected
Wall Motion Score < 14	62	46	46.76057
Wall Motion Score $\quad 14$	68	42	41.23943
Fractional Shortening < 0.2	61	33	30.98374
Fractional Shortening $\quad 0.2$	69	55	57.01626

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\begin{center}\includegraphics{markdown_files/figure-latex/unnamed-chunk-1-2} \end{center}

\begin{center}\includegraphics{markdown_files/figure-latex/unnamed-chunk-1-3} \end{center}

The table below summarizes the parameter point estimates and corresponding 95% confidence intervals.

\begin{tabular}{l|r|r|r|r|r}
\hline
Model & Quantile & Point Estimate & 95\% LCL & 95\% UCL & Interval Length\\
\hline
Weibull & 0.25 & 22.42 & 19.96 & 25.19 & 5.23\\
\hline
NA & 0.50 & 30.32 & 27.86 & 33.01 & 5.15\\
\hline
NA & 0.75 & 38.47 & 35.71 & 41.44 & 5.72\\
\hline
Log-normal & 0.25 & 20.73 & 18.77 & 22.89 & 4.11\\
\hline
NA & 0.50 & 27.97 & 25.54 & 30.63 & 5.09\\
\hline
NA & 0.75 & 37.74 & 34.06 & 41.83 & 7.77\\
\hline
Log-logistic & 0.25 & 21.90 & 19.77 & 24.27 & 4.50\\
\hline
NA & 0.50 & 28.88 & 26.41 & 31.59 & 5.18\\
\hline
NA & 0.75 & 38.09 & 34.45 & 42.12 & 7.67\\
\hline
\end{tabular}

Q-Q plots were also prepared for each distribution, and are provided in the Appendix. Based on inspecti

Regression Analysis - Cox Proportional Hazard Modeling

Regression analysis was conducted to identify the relationship between potential predictor variables an

\begin{description}
  \item[$\bullet$] Age
  \item[$\bullet$] Pericardial Effusion
  \item[$\bullet$] Wall Motion Score
  \item[$\bullet$] Fractional Shortening
\end{description}

A model employing all of the covariates listed above was created. In order to test validit of the propo

This limitation was addressed through the identification of survival time subsets in which covariates m

The selected time subsets were obtained as follows:

\begin{description}
 \item[$Subset \:1: t \leq {26} \:{months}$]
 \item[$Subset \:2:26 \:{months}< t < 46 \:{months}$]
 \item[$Subset \:3: 46 \: months \leq t$]
\end{description}

Within each time subset, the proportional hazard assumption was tested for each of the four covariates a

The three models are summarized below:

\begin{tabular}{l|l|l|l|l|l|l|l|l|l|l}
\hline
Characteristic & **HR** & **95\% CI** & **p-value** & **HR** & **95\% CI** & **p-value** & **HR** &
\hline
Wall_Motion_Score & 0.85 & 0.69, 1.05 & 0.13 & 0.90 & 0.79, 1.02 & 0.11 & & & \\
\hline
Fractional_Shortening & 0.00 & 0.00, 0.01 & 0.009 & & & & & & & \\
\hline
Wall_Motion_Score * Fractional_Shortening & 4.31 & 1.51, 12.4 & 0.006 & & & & & & & \\
\hline
Age & & & & & & & 0.96 & 0.92, 1.00 & 0.051\\
\hline
\end{tabular}
For Model 1, the significant predictors of survival time are identified as Fractional Shortening and its

For Model 2, the significant predictor of survival time is identified as patient age. Age is found to ha

For subset 3, the sample size of events in the survival data subset was small (n=11) and a significant n

Model residual diagnostics were assessed for all three models. Models 1 and 2 showed overall good fit to

Discussion

Explanation of results
In our non-parametric analysis, median survival times for nearly all of the stratification elements shou

In the parametric analysis, it was found that the survivor data is well-described by the Weibull distril

Summary of Limitations
Very clearly, our data is smaller than we hoped for, both in the number of observations and in the avail

A particular limitation related to subgroup dimension was identified through the stratification analysis

Finally, the given dataset did not have clear statements as to what data collection methods were used. C

Conclusion
This study identified a variety of properties of the post-myocardial infarction survival data. The overa

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Appendix

References

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Dataset Variable Summary

\begin{longtabu} to \linewidth {>{\raggedright}X>{\raggedright}X>{\raggedright}X}
\caption{\label{tab:Dataset.summary}Summary of Dataset Covariates}\\

```
\toprule
Variable & Label & Definition\\
\midrule
\endfirsthead
\caption[]{Summary of Dataset Covariates \textit{(continued)}}\\
\toprule
Variable & Label & Definition\\
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Survival & Survival & The number of months the patints survived, post-myocardial infarction.\\
\addlinespace
Status & Status & Censorship status. 0 denotes that a patient is a censored while 1 denotes that a pati
\addlinespace
Alive at the end of Survival Period & Alive.E & Binary variable. 0 denotes that patient is alive at the
\addlinespace
Patient Age & Age & The age in years when a myocardial infarction occurs.\\
\addlinespace
Age Group & Age.S & 0 denotes younger than 55 years . 1 denotes 55 - 70 years. 2 denotes older than 70\
\addlinespace
Pericardial Effusion & P.Effusion & Binary variable. Pericardial effusion is excess fluid surrounding t
\addlinespace
Fractional Shortening & F.Shortening & Fractional shortening is a measure of contractility around the h
\addlinespace
E-Point Septal Separation & EPSS & E-point septal separation is an addition measure of heart contracti
\addlinespace
Left Ventricular End-Diastolic Dimension & LVDD & Left ventricular end-diastolic dimension is the measu
\addlinespace
Wall Motion Score & WMS & Wall motion score is a measure of how the segments of the left ventricle are
\addlinespace
Wall Motion Index & WMI & Wall motion index is the wall motion score divided by the number of segments
\addlinespace
Wall Motion Strata & WMS.S & 0 denotes score less than 11, 1 denotes score 12-14, 2 denotes score greate
\end{longtabu}


## Original Dataset


\begin{longtabu} to \linewidth {>{\raggedleft}X>{\raggedleft}X>{\raggedleft}X>{\raggedleft}X>{\raggedle
\caption{\label{tab:Dataset.actual}Original Dataset}\\
\toprule
Survival & Status & Alive.E & Age & Age.Strata & P.Effusion & F.Shortening & EPSS & LVDD & WMS & WMI & W
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\endfirsthead
\caption[]{Original Dataset \textit{(continued)}}\\
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Survival & Status & Alive.E & Age & Age.Strata & P.Effusion & F.Shortening & EPSS & LVDD & WMS & WMI & W
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1.00 & 0 & 1 & 60.00 & 1 & 0 & 0.010 & 24.600 & 5.650 & 39.00 & 3.000 & 1\\
10.00 & 1 & 0 & 66.00 & 2 & 0 & 0.290 & 15.600 & 6.150 & 14.00 & 1.000 & 0\\
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27.00 & 1 & 0 & 62.00 & 1 & 0 & 0.220 & 12.100 & 3.920 & 11.00 & 1.000 & 0\\
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25.00 & 1 & 0 & 59.00 & 1 & 1 & 0.400 & 9.200 & 5.360 & 12.00 & 1.000 & 0\\
27.00 & 1 & 0 & 57.00 & 1 & 0 & 0.290 & 9.400 & 4.770 & 9.00 & 1.000 & 0\\
34.00 & 1 & 0 & 62.00 & 1 & 1 & 0.190 & 28.900 & 6.630 & 19.50 & 1.950 & 1\\
37.00 & 1 & 0 & NA & 2 & 0 & 0.260 & 0.000 & 4.380 & 9.00 & 1.000 & 0\\
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28.00 & 1 & 0 & NA & 2 & 0 & 0.230 & 19.100 & 5.490 & 12.00 & 1.200 & 0\\
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## Imputed Dataset


\begin{longtabu} to \linewidth {>{\raggedleft}X>{\raggedleft}X>{\raggedleft}X>{\raggedleft}X>{\raggedleft}X>{\raggedle
\caption{\label{tab:imp.table}Imputed Dataset}\\
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Survival & Status & Alive.E & Age & P.Effusion & F.Shortening & EPSS & LVDD & WMS & WMI & Age.s & WMS.s
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\endfirsthead
\caption[]{Imputed Dataset \textit{(continued)}}\\
\toprule
Survival & Status & Alive.E & Age & P.Effusion & F.Shortening & EPSS & LVDD & WMS & WMI & Age.s & WMS.s
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\endfoot
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10.00 & 1 & 0 & 66.00 & 0 & 0.29 & 15.60 & 6.15 & 14.00 & 1.00 & 1 & 1 & 1 & 1 & 1\\
\addlinespace
45.00 & 1 & 0 & 63.00 & 0 & 0.15 & 13.00 & 4.57 & 13.00 & 1.08 & 1 & 0 & 0 & 0 & 1\\
22.00 & 1 & 0 & 57.00 & 0 & 0.13 & 18.60 & 4.37 & 12.33 & 1.37 & 0 & 0 & 0 & 0 & 1\\
53.00 & 1 & 0 & 70.00 & 0 & 0.10 & 9.80 & 5.30 & 23.00 & 2.30 & 1 & 1 & 0 & 1 & 0\\
38.00 & 1 & 0 & 68.00 & 0 & 0.29 & 6.89 & 4.41 & 14.00 & 1.17 & 1 & 1 & 1 & 0 & 0\\
26.00 & 1 & 0 & 79.00 & 0 & 0.17 & 11.90 & 5.15 & 10.50 & 1.05 & 1 & 0 & 0 & 1 & 1\\
\addlinespace
9.00 & 1 & 0 & 73.00 & 0 & 0.12 & 21.14 & 6.78 & 16.67 & 1.39 & 1 & 1 & 0 & 1 & 1\\
26.00 & 1 & 0 & 72.00 & 0 & 0.19 & 12.00 & 5.02 & 13.00 & 1.18 & 1 & 0 & 0 & 1 & 1\\
0.50 & 0 & 1 & 59.00 & 0 & 0.13 & 16.40 & 4.96 & 17.83 & 1.37 & 0 & 1 & 0 & 1 & 1\\
12.00 & 1 & 0 & 67.00 & 1 & 0.11 & 10.30 & 4.68 & 11.00 & 1.00 & 1 & 0 & 0 & 0 & 0\\
49.00 & 1 & 0 & 51.00 & 0 & 0.16 & 13.20 & 5.26 & 11.00 & 1.00 & 0 & 0 & 0 & 1 & 1\\
\addlinespace
0.75 & 0 & 1 & 50.00 & 0 & 0.14 & 11.40 & 4.75 & 10.00 & 2.50 & 0 & 0 & 0 & 1 & 1\\
49.00 & 1 & 0 & 70.00 & 1 & 0.25 & 9.70 & 5.57 & 5.50 & 1.10 & 1 & 0 & 1 & 1 & 0\\
47.00 & 1 & 0 & 65.00 & 0 & 0.36 & 8.80 & 5.78 & 12.00 & 1.00 & 1 & 0 & 1 & 1 & 0\\
41.00 & 1 & 0 & 78.00 & 0 & 0.06 & 16.10 & 5.62 & 13.67 & 1.37 & 1 & 0 & 0 & 1 & 1\\
0.25 & 0 & 1 & 86.00 & 0 & 0.22 & 12.20 & 5.20 & 24.00 & 2.18 & 1 & 1 & 1 & 1 & 1\\
\addlinespace
33.00 & 1 & 0 & 56.00 & 0 & 0.25 & 11.00 & 4.72 & 11.00 & 1.00 & 0 & 0 & 1 & 0 & 0\\
29.00 & 1 & 0 & 60.00 & 0 & 0.12 & 10.20 & 4.31 & 15.00 & 1.67 & 0 & 1 & 0 & 0 & 0\\
41.00 & 1 & 0 & 59.00 & 0 & 0.29 & 7.50 & 4.75 & 13.00 & 1.08 & 0 & 0 & 1 & 1 & 0\\
26.00 & 1 & 0 & 50.00 & 0 & 0.06 & 30.10 & 5.95 & 21.50 & 2.39 & 0 & 1 & 0 & 1 & 1\\
15.00 & 1 & 0 & 54.00 & 0 & 0.22 & 17.90 & 4.54 & 16.50 & 1.18 & 0 & 1 & 1 & 0 & 1\\
\addlinespace
```

```
0.25 & 0 & 1 & 68.00 & 0 & 0.22 & 21.70 & 4.85 & 15.00 & 1.15 & 1 & 1 & 1 & 1 & 1\\
0.03 & 0 & 1 & 72.91 & 0 & 0.26 & 19.40 & 4.77 & 21.00 & 2.10 & 1 & 1 & 1 & 1 & 1\\
12.00 & 1 & 0 & 64.00 & 0 & 0.20 & 7.10 & 4.58 & 14.00 & 1.00 & 1 & 1 & 1 & 0 & 0\\
32.00 & 1 & 0 & 63.00 & 0 & 0.20 & 5.00 & 5.20 & 8.00 & 1.00 & 1 & 0 & 1 & 1 & 0\\
32.00 & 1 & 0 & 65.00 & 0 & 0.06 & 23.60 & 6.74 & 12.00 & 1.09 & 1 & 0 & 0 & 1 & 1\\
\addlinespace
27.00 & 1 & 0 & 54.00 & 1 & 0.07 & 16.80 & 4.16 & 18.00 & 1.50 & 0 & 1 & 0 & 0 & 1\\
23.00 & 1 & 0 & 62.00 & 0 & 0.25 & 6.00 & 4.48 & 11.00 & 1.00 & 0 & 0 & 1 & 0 & 0\\
0.75 & 0 & 1 & 78.00 & 0 & 0.05 & 10.00 & 4.44 & 15.00 & 1.36 & 1 & 1 & 0 & 0 & 0\\
0.75 & 0 & 1 & 61.00 & 0 & 0.13 & 18.21 & 5.31 & 28.00 & 2.33 & 0 & 1 & 0 & 1 & 1\\
34.00 & 1 & 0 & 52.00 & 0 & 0.14 & 25.00 & 6.21 & 11.50 & 1.15 & 0 & 0 & 0 & 1 & 1\\
\addlinespace
1.00 & 0 & 1 & 73.00 & 0 & 0.05 & 14.80 & 4.14 & 15.50 & 1.41 & 1 & 1 & 0 & 0 & 1\\
21.00 & 0 & 1 & 70.00 & 1 & 0.16 & 19.20 & 5.25 & 11.00 & 1.00 & 1 & 0 & 0 & 1 & 1\\
55.00 & 1 & 0 & 55.00 & 0 & 0.28 & 5.50 & 4.48 & 22.00 & 1.83 & 0 & 1 & 1 & 0 & 0\\
15.00 & 0 & 1 & 60.00 & 0 & 0.18 & 8.70 & 4.56 & 13.50 & 1.04 & 0 & 0 & 0 & 0 & 0\\
0.50 & 0 & 1 & 67.00 & 0 & 0.16 & 11.30 & 5.16 & 13.00 & 1.00 & 1 & 0 & 0 & 1 & 1\\
\addlinespace
35.00 & 1 & 0 & 64.00 & 0 & 0.30 & 6.60 & 4.36 & 14.00 & 1.27 & 1 & 1 & 1 & 0 & 0\\
53.00 & 1 & 0 & 59.00 & 0 & 0.34 & 9.10 & 4.04 & 9.00 & 1.00 & 0 & 0 & 1 & 0 & 0\\
33.00 & 1 & 0 & 46.00 & 0 & 0.27 & 16.50 & 5.36 & 12.67 & 1.06 & 0 & 0 & 1 & 1 & 1\\
33.00 & 1 & 0 & 63.00 & 0 & 0.25 & 5.60 & 3.87 & 18.00 & 1.50 & 1 & 1 & 1 & 0 & 0\\
40.00 & 0 & 1 & 74.00 & 0 & 0.20 & 4.80 & 4.56 & 12.50 & 1.04 & 1 & 0 & 1 & 0 & 0\\
\addlinespace
33.00 & 1 & 0 & 59.00 & 0 & 0.50 & 9.10 & 3.42 & 18.00 & 1.50 & 0 & 1 & 1 & 0 & 0\\
5.00 & 0 & 1 & 65.00 & 1 & 0.16 & 8.50 & 5.47 & 16.00 & 1.45 & 1 & 1 & 0 & 1 & 0\\
4.00 & 0 & 1 & 58.00 & 0 & 0.17 & 28.90 & 6.73 & 26.08 & 2.01 & 0 & 1 & 0 & 1 & 1\\
31.00 & 1 & 0 & 53.00 & 0 & 0.17 & 10.30 & 4.69 & 10.00 & 1.00 & 0 & 0 & 0 & 0 & 0\\
33.00 & 1 & 0 & 66.00 & 0 & 0.20 & 8.12 & 4.23 & 12.00 & 1.00 & 1 & 0 & 1 & 0 & 0\\
\addlinespace
22.00 & 1 & 0 & 70.00 & 0 & 0.38 & 0.00 & 4.55 & 10.00 & 1.00 & 1 & 0 & 1 & 0 & 0\\
25.00 & 1 & 0 & 62.00 & 0 & 0.26 & 11.80 & 4.87 & 11.00 & 1.00 & 0 & 0 & 1 & 1 & 1\\
1.25 & 0 & 1 & 63.00 & 0 & 0.30 & 6.90 & 3.52 & 18.16 & 1.51 & 1 & 1 & 1 & 0 & 0\\
24.00 & 1 & 0 & 59.00 & 0 & 0.17 & 14.30 & 5.49 & 13.50 & 1.50 & 0 & 0 & 0 & 1 & 1\\
25.00 & 1 & 0 & 57.00 & 0 & 0.23 & 9.70 & 4.29 & 11.00 & 1.00 & 0 & 0 & 1 & 0 & 0\\
\addlinespace
24.00 & 1 & 0 & 57.00 & 0 & 0.04 & 7.00 & 4.12 & 13.50 & 1.23 & 0 & 0 & 0 & 0 & 0\\
0.75 & 0 & 1 & 78.00 & 0 & 0.23 & 40.00 & 6.23 & 14.00 & 1.40 & 1 & 1 & 1 & 1 & 1\\
3.00 & 0 & 1 & 62.00 & 0 & 0.26 & 7.60 & 4.42 & 14.00 & 1.00 & 0 & 1 & 1 & 0 & 0\\
27.00 & 1 & 0 & 62.00 & 0 & 0.22 & 12.10 & 3.92 & 11.00 & 1.00 & 0 & 0 & 1 & 0 & 1\\
13.00 & 1 & 0 & 66.00 & 0 & 0.24 & 13.60 & 4.38 & 22.00 & 2.20 & 1 & 1 & 1 & 0 & 1\\
\addlinespace
36.00 & 1 & 0 & 61.00 & 0 & 0.27 & 9.00 & 4.06 & 12.00 & 1.00 & 0 & 0 & 1 & 0 & 0\\
25.00 & 1 & 0 & 59.00 & 1 & 0.40 & 9.20 & 5.36 & 12.00 & 1.00 & 0 & 0 & 1 & 1 & 0\\
27.00 & 1 & 0 & 57.00 & 0 & 0.29 & 9.40 & 4.77 & 9.00 & 1.00 & 0 & 0 & 1 & 1 & 0\\
34.00 & 1 & 0 & 62.00 & 1 & 0.19 & 28.90 & 6.63 & 19.50 & 1.95 & 0 & 1 & 0 & 1 & 1\\
37.00 & 1 & 0 & 69.34 & 0 & 0.26 & 0.00 & 4.38 & 9.00 & 1.00 & 1 & 0 & 1 & 0 & 0\\
\addlinespace
34.00 & 1 & 0 & 54.00 & 0 & 0.43 & 9.30 & 4.79 & 10.00 & 1.00 & 0 & 0 & 1 & 1 & 0\\
28.00 & 0 & 1 & 62.00 & 1 & 0.24 & 28.60 & 5.86 & 21.50 & 1.95 & 0 & 1 & 1 & 1 & 1\\
28.00 & 1 & 0 & 69.19 & 0 & 0.23 & 19.10 & 5.49 & 12.00 & 1.20 & 1 & 0 & 1 & 1 & 1\\
17.00 & 1 & 0 & 64.00 & 0 & 0.15 & 6.60 & 4.17 & 14.00 & 1.27 & 1 & 1 & 0 & 0 & 0\\
38.00 & 1 & 0 & 57.00 & 1 & 0.12 & 0.00 & 2.32 & 16.50 & 1.38 & 0 & 1 & 0 & 0 & 0\\
\addlinespace
```

```
31.00 & 1 & 0 & 61.00 & 0 & 0.18 & 0.00 & 4.48 & 11.00 & 1.38 & 0 & 0 & 0 & 0 & 0\\
12.00 & 1 & 0 & 61.00 & 1 & 0.19 & 13.20 & 5.04 & 19.00 & 1.73 & 0 & 1 & 0 & 1 & 1\\
36.00 & 1 & 0 & 48.00 & 0 & 0.15 & 12.00 & 3.66 & 10.00 & 1.00 & 0 & 0 & 0 & 0 & 1\\
17.00 & 1 & 0 & 69.67 & 0 & 0.09 & 6.80 & 4.96 & 13.00 & 1.08 & 1 & 0 & 0 & 1 & 0\\
21.00 & 1 & 0 & 61.00 & 0 & 0.14 & 25.50 & 5.16 & 14.00 & 1.27 & 0 & 1 & 0 & 1 & 1\\
\addlinespace
7.50 & 0 & 1 & 64.00 & 0 & 0.24 & 12.90 & 4.72 & 12.00 & 1.00 & 1 & 0 & 1 & 0 & 1\\
41.00 & 1 & 0 & 64.00 & 0 & 0.28 & 5.40 & 5.47 & 11.00 & 1.10 & 1 & 0 & 1 & 1 & 0\\
36.00 & 1 & 0 & 69.00 & 0 & 0.20 & 7.00 & 5.05 & 14.50 & 1.21 & 1 & 1 & 1 & 1 & 0\\
22.00 & 1 & 0 & 57.00 & 0 & 0.14 & 16.10 & 4.36 & 15.00 & 1.36 & 0 & 1 & 0 & 0 & 1\\
20.00 & 1 & 0 & 62.00 & 0 & 0.15 & 0.00 & 4.51 & 15.50 & 1.41 & 0 & 1 & 0 & 0 & 0\\*
\end{longtabu}

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## Table of Kaplan-Meier Estimators

\begin{table}[!h]

\caption{\label{tab:km.table}Kaplan-Meier Estimate Summary}
\centering
\begin{tabular}[t]{r|r|r|r|r|r|r}
\hline
Ni & Di & Ci & Survival & Std. Err & 95\% LCL & 95\% UCL\\
\hline
130 & 0 & 1 & 1.0000000 & 0.0000000 & 1.0000000 & 1.0000000\\
\hline
129 & 0 & 4 & 1.0000000 & 0.0000000 & 1.0000000 & 1.0000000\\
\hline
125 & 0 & 6 & 1.0000000 & 0.0000000 & 1.0000000 & 1.0000000\\
\hline
119 & 0 & 6 & 1.0000000 & 0.0000000 & 1.0000000 & 1.0000000\\
\hline
113 & 0 & 6 & 1.0000000 & 0.0000000 & 1.0000000 & 1.0000000\\
\hline
107 & 0 & 1 & 1.0000000 & 0.0000000 & 1.0000000 & 1.0000000\\
\hline
106 & 0 & 2 & 1.0000000 & 0.0000000 & 1.0000000 & 1.0000000\\
\hline
104 & 0 & 2 & 1.0000000 & 0.0000000 & 1.0000000 & 1.0000000\\
\hline
102 & 0 & 1 & 1.0000000 & 0.0000000 & 1.0000000 & 1.0000000\\
\hline
101 & 0 & 2 & 1.0000000 & 0.0000000 & 1.0000000 & 1.0000000\\
\hline
99 & 0 & 1 & 1.0000000 & 0.0000000 & 1.0000000 & 1.0000000\\
\hline
98 & 0 & 1 & 1.0000000 & 0.0000000 & 1.0000000 & 1.0000000\\
\hline
97 & 1 & 0 & 0.9896907 & 0.0103628 & 0.9697921 & 1.0000000\\
\hline
96 & 2 & 1 & 0.9690722 & 0.0181389 & 0.9352253 & 1.0000000\\
\hline
93 & 1 & 0 & 0.9586520 & 0.0211163 & 0.9197860 & 0.9991604\\
```

```
\hline
92 & 4 & 0 & 0.9169715 & 0.0306589 & 0.8634932 & 0.9737618\\
\hline
88 & 2 & 0 & 0.8961312 & 0.0347021 & 0.8372075 & 0.9592021\\
\hline
86 & 1 & 1 & 0.8857111 & 0.0366202 & 0.8243677 & 0.9516193\\
\hline
84 & 3 & 0 & 0.8540786 & 0.0422132 & 0.7862595 & 0.9277475\\
\hline
81 & 2 & 0 & 0.8329902 & 0.0457657 & 0.7615248 & 0.9111624\\
\hline
79 & 3 & 1 & 0.8013577 & 0.0509330 & 0.7252240 & 0.8854839\\
\hline
75 & 0 & 1 & 0.8013577 & 0.0509330 & 0.7252240 & 0.8854839\\
\hline
74 & 1 & 1 & 0.7905285 & 0.0527189 & 0.7129238 & 0.8765809\\
\hline
72 & 1 & 1 & 0.7795490 & 0.0545427 & 0.7005136 & 0.8675015\\
\hline
70 & 3 & 1 & 0.7461397 & 0.0601212 & 0.6632005 & 0.8394512\\
\hline
66 & 1 & 0 & 0.7348346 & 0.0620295 & 0.6507137 & 0.8298302\\
\hline
65 & 3 & 0 & 0.7009191 & 0.0677649 & 0.6137427 & 0.8004782\\
\hline
62 & 4 & 0 & 0.6556985 & 0.0755277 & 0.5654770 & 0.7603149\\
\hline
58 & 5 & 0 & 0.5991728 & 0.0856211 & 0.5066071 & 0.7086518\\
\hline
53 & 4 & 0 & 0.5539522 & 0.0941871 & 0.4605747 & 0.6662612\\
\hline
49 & 1 & 1 & 0.5426471 & 0.0964177 & 0.4492070 & 0.6555237\\
\hline
47 & 4 & 0 & 0.4964643 & 0.1061866 & 0.4031827 & 0.6113280\\
\hline
43 & 3 & 0 & 0.4618273 & 0.1141043 & 0.3692784 & 0.5775709\\
\hline
40 & 3 & 0 & 0.4271902 & 0.1226655 & 0.3358987 & 0.5432933\\
\hline
37 & 5 & 0 & 0.3694618 & 0.1388157 & 0.2814553 & 0.4849865\\
\hline
32 & 3 & 0 & 0.3348248 & 0.1500085 & 0.2495342 & 0.4492676\\
\hline
29 & 2 & 0 & 0.3117334 & 0.1582935 & 0.2285829 & 0.4251312\\
\hline
27 & 4 & 0 & 0.2655507 & 0.1774769 & 0.1875335 & 0.3760244\\
\hline
23 & 2 & 0 & 0.2424593 & 0.1887825 & 0.1674738 & 0.3510192\\
\hline
21 & 2 & 0 & 0.2193680 & 0.2016218 & 0.1477585 & 0.3256822\\
\hline
19 & 1 & 1 & 0.2078223 & 0.2087471 & 0.1380404 & 0.3128801\\
\hline
17 & 3 & 0 & 0.1711478 & 0.2370240 & 0.1075514 & 0.2723494\\
```

```
\hline
14 & 1 & 0 & 0.1589229 & 0.2483443 & 0.0976777 & 0.2585697\\
\hline
13 & 1 & 0 & 0.1466981 & 0.2609313 & 0.0879669 & 0.2446412\\
\hline
12 & 1 & 0 & 0.1344732 & 0.2750653 & 0.0784332 & 0.2305536\\
\hline
11 & 1 & 0 & 0.1222484 & 0.2911216 & 0.0690939 & 0.2162949\\
\hline
10 & 1 & 0 & 0.1100236 & 0.3096174 & 0.0599707 & 0.2018517\\
\hline
9 & 2 & 0 & 0.0855739 & 0.3572240 & 0.0424885 & 0.1723498\\
\hline
7 & 1 & 0 & 0.0733490 & 0.3891253 & 0.0342114 & 0.1572601\\
\hline
6 & 2 & 0 & 0.0488994 & 0.4845119 & 0.0189185 & 0.1263923\\
\hline
4 & 2 & 0 & 0.0244497 & 0.6962412 & 0.0062464 & 0.0957006\\
\hline
2 & 1 & 0 & 0.0122248 & 0.9923466 & 0.0017481 & 0.0854929\\
\hline
1 & 1 & 0 & 0.0000000 & Inf & NA & NA\\
\hline
\end{tabular}
\end{table}

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## Parametric Model Q-Q Plots

Q-Q plots for each of the three assessed parametric models are provided below. We see that the Weibull m

[1] "Smallest observation is censored!"
       logtime       sevq
1   -3.5065579       -Inf
2   -1.3862944       -Inf
3   -1.3862944       -Inf
4   -1.3862944       -Inf
5   -1.3862944       -Inf
6   -0.6931472       -Inf
7   -0.6931472       -Inf
8   -0.6931472       -Inf
9   -0.6931472       -Inf
10  -0.6931472       -Inf
11  -0.6931472       -Inf
12  -0.2876821       -Inf
13  -0.2876821       -Inf
14  -0.2876821       -Inf
15  -0.2876821       -Inf
16  -0.2876821       -Inf
17  -0.2876821       -Inf
18   0.0000000       -Inf
```

19	0.0000000	-Inf
20	0.0000000	-Inf
21	0.0000000	-Inf
22	0.0000000	-Inf
23	0.0000000	-Inf
24	0.2231436	-Inf
25	0.6931472	-Inf
26	0.6931472	-Inf
27	1.0986123	-Inf
28	1.0986123	-Inf
29	1.3862944	-Inf
30	1.6094379	-Inf
31	1.6094379	-Inf
32	1.9459101	-Inf
33	2.0149030	-Inf
34	2.1972246	-4.5695341
35	2.3025851	-3.4604317
36	2.3025851	-3.4604317
37	2.3025851	-3.4604317
38	2.3978953	-3.1646928
39	2.4849066	-2.4455451
40	2.4849066	-2.4455451
41	2.4849066	-2.4455451
42	2.4849066	-2.4455451
43	2.5649494	-2.2102941
44	2.5649494	-2.2102941
45	2.7080502	-2.1089574
46	2.7080502	-2.1089574
47	2.7725887	-1.8468574
48	2.7725887	-1.8468574
49	2.7725887	-1.8468574
50	2.8332133	-1.6997271
51	2.8332133	-1.6997271
52	2.9444390	-1.5075680
53	2.9444390	-1.5075680
54	2.9444390	-1.5075680
55	2.9444390	-1.5075680
56	2.9704145	-1.5075680
57	2.9957323	-1.4479419
58	2.9957323	-1.4479419
59	3.0445224	-1.3901426
60	3.0445224	-1.3901426
61	3.0910425	-1.2281207
62	3.0910425	-1.2281207
63	3.0910425	-1.2281207
64	3.0910425	-1.2281207
65	3.1354942	-1.1772988
66	3.1780538	-1.0346161
67	3.1780538	-1.0346161
68	3.1780538	-1.0346161
69	3.2188758	-0.8626217
70	3.2188758	-0.8626217
71	3.2188758	-0.8626217
72	3.2188758	-0.8626217

73	3.2580965	-0.6690299
74	3.2580965	-0.6690299
75	3.2580965	-0.6690299
76	3.2580965	-0.6690299
77	3.2580965	-0.6690299
78	3.2958369	-0.5264862
79	3.2958369	-0.5264862
80	3.2958369	-0.5264862
81	3.2958369	-0.5264862
82	3.3322045	-0.4921738
83	3.3322045	-0.4921738
84	3.3672958	-0.3563270
85	3.3672958	-0.3563270
86	3.3672958	-0.3563270
87	3.3672958	-0.3563270
88	3.4339872	-0.2580401
89	3.4339872	-0.2580401
90	3.4339872	-0.2580401
91	3.4657359	-0.1619005
92	3.4657359	-0.1619005
93	3.4657359	-0.1619005
94	3.4965076	-0.0043014
95	3.4965076	-0.0043014
96	3.4965076	-0.0043014
97	3.4965076	-0.0043014
98	3.4965076	-0.0043014
99	3.5263605	0.0899759
100	3.5263605	0.0899759
101	3.5263605	0.0899759
102	3.5553481	0.1532419
103	3.5553481	0.1532419
104	3.5835189	0.2821288
105	3.5835189	0.2821288
106	3.5835189	0.2821288
107	3.5835189	0.2821288
108	3.6109179	0.3484864
109	3.6109179	0.3484864
110	3.6375862	0.4167378
111	3.6375862	0.4167378
112	3.6888795	0.4517582
113	3.6888795	0.4517582
114	3.7135721	0.5682799
115	3.7135721	0.5682799
116	3.7135721	0.5682799
117	3.7841896	0.6094046
118	3.8066625	0.6520015
119	3.8286414	0.6963371
120	3.8501476	0.7427467
121	3.8712010	0.7916617
122	3.8918203	0.8995006
123	3.8918203	0.8995006
124	3.9120230	0.9603175
125	3.9512437	1.1045914
126	3.9512437	1.1045914

```
127  3.9702919  1.3113386
128  3.9702919  1.3113386
129  4.0073332  1.4825780
130  4.0430513        Inf
```

```
\begin{center}\includegraphics{markdown_files/figure-latex/unnamed-chunk-4-1} \end{center}
```

```
[1] "Q-Q plot for weibull done"
[1] "Smallest observation is censored!"
       logtime         sevq
1   -3.5065579         -Inf
2   -1.3862944         -Inf
3   -1.3862944         -Inf
4   -1.3862944         -Inf
5   -1.3862944         -Inf
6   -0.6931472         -Inf
7   -0.6931472         -Inf
8   -0.6931472         -Inf
9   -0.6931472         -Inf
10  -0.6931472         -Inf
11  -0.6931472         -Inf
12  -0.2876821         -Inf
13  -0.2876821         -Inf
14  -0.2876821         -Inf
15  -0.2876821         -Inf
16  -0.2876821         -Inf
17  -0.2876821         -Inf
18   0.0000000         -Inf
19   0.0000000         -Inf
20   0.0000000         -Inf
21   0.0000000         -Inf
22   0.0000000         -Inf
23   0.0000000         -Inf
24   0.2231436         -Inf
25   0.6931472         -Inf
26   0.6931472         -Inf
27   1.0986123         -Inf
28   1.0986123         -Inf
29   1.3862944         -Inf
30   1.6094379         -Inf
31   1.6094379         -Inf
32   1.9459101         -Inf
33   2.0149030         -Inf
34   2.1972246 -2.314897235
35   2.3025851 -1.867328913
36   2.3025851 -1.867328913
37   2.3025851 -1.867328913
38   2.3978953 -1.735253400
39   2.4849066 -1.384985248
40   2.4849066 -1.384985248
41   2.4849066 -1.384985248
42   2.4849066 -1.384985248
43   2.5649494 -1.259811137
```

```
44   2.5649494 -1.259811137
45   2.7080502 -1.204030570
46   2.7080502 -1.204030570
47   2.7725887 -1.054087534
48   2.7725887 -1.054087534
49   2.7725887 -1.054087534
50   2.8332133 -0.966049199
51   2.8332133 -0.966049199
52   2.9444390 -0.846480688
53   2.9444390 -0.846480688
54   2.9444390 -0.846480688
55   2.9444390 -0.846480688
56   2.9704145 -0.846480688
57   2.9957323 -0.808256465
58   2.9957323 -0.808256465
59   3.0445224 -0.770670800
60   3.0445224 -0.770670800
61   3.0910425 -0.662391162
62   3.0910425 -0.662391162
63   3.0910425 -0.662391162
64   3.0910425 -0.662391162
65   3.1354942 -0.627501031
66   3.1780538 -0.527045857
67   3.1780538 -0.527045857
68   3.1780538 -0.527045857
69   3.2188758 -0.400751729
70   3.2188758 -0.400751729
71   3.2188758 -0.400751729
72   3.2188758 -0.400751729
73   3.2580965 -0.251206585
74   3.2580965 -0.251206585
75   3.2580965 -0.251206585
76   3.2580965 -0.251206585
77   3.2580965 -0.251206585
78   3.2958369 -0.135653042
79   3.2958369 -0.135653042
80   3.2958369 -0.135653042
81   3.2958369 -0.135653042
82   3.3322045 -0.107104766
83   3.3322045 -0.107104766
84   3.3672958  0.008862707
85   3.3672958  0.008862707
86   3.3672958  0.008862707
87   3.3672958  0.008862707
88   3.4339872  0.095831270
89   3.4339872  0.095831270
90   3.4339872  0.095831270
91   3.4657359  0.183532159
92   3.4657359  0.183532159
93   3.4657359  0.183532159
94   3.4965076  0.333279032
95   3.4965076  0.333279032
96   3.4965076  0.333279032
97   3.4965076  0.333279032
```

```
98   3.4965076  0.333279032
99   3.5263605  0.426629000
100  3.5263605  0.426629000
101  3.5263605  0.426629000
102  3.5553481  0.490942887
103  3.5553481  0.490942887
104  3.5835189  0.626325621
105  3.5835189  0.626325621
106  3.5835189  0.626325621
107  3.5835189  0.626325621
108  3.6109179  0.698413469
109  3.6109179  0.698413469
110  3.6375862  0.774329562
111  3.6375862  0.774329562
112  3.6888795  0.814000679
113  3.6888795  0.814000679
114  3.7135721  0.949639380
115  3.7135721  0.949639380
116  3.7135721  0.949639380
117  3.7841896  0.998894416
118  3.8066625  1.050700511
119  3.8286414  1.105491949
120  3.8501476  1.163820405
121  3.8712010  1.226402832
122  3.8918203  1.368525132
123  3.8918203  1.368525132
124  3.9120230  1.451293751
125  3.9512437  1.655620380
126  3.9512437  1.655620380
127  3.9702919  1.969468118
128  3.9702919  1.969468118
129  4.0073332  2.249988425
130  4.0430513         Inf
```

\begin{center}\includegraphics{markdown_files/figure-latex/unnamed-chunk-4-2} \end{center}

```
[1] "Q-Q plot for lognormal done"
[1] "Smallest observation is censored!"
       logtime        sevq
1   -3.5065579        -Inf
2   -1.3862944        -Inf
3   -1.3862944        -Inf
4   -1.3862944        -Inf
5   -1.3862944        -Inf
6   -0.6931472        -Inf
7   -0.6931472        -Inf
8   -0.6931472        -Inf
9   -0.6931472        -Inf
10  -0.6931472        -Inf
11  -0.6931472        -Inf
12  -0.2876821        -Inf
13  -0.2876821        -Inf
14  -0.2876821        -Inf
```

15	-0.2876821	-Inf
16	-0.2876821	-Inf
17	-0.2876821	-Inf
18	0.0000000	-Inf
19	0.0000000	-Inf
20	0.0000000	-Inf
21	0.0000000	-Inf
22	0.0000000	-Inf
23	0.0000000	-Inf
24	0.2231436	-Inf
25	0.6931472	-Inf
26	0.6931472	-Inf
27	1.0986123	-Inf
28	1.0986123	-Inf
29	1.3862944	-Inf
30	1.6094379	-Inf
31	1.6094379	-Inf
32	1.9459101	-Inf
33	2.0149030	-Inf
34	2.1972246	-4.56434819
35	2.3025851	-3.44468249
36	2.3025851	-3.44468249
37	2.3025851	-3.44468249
38	2.3978953	-3.14350494
39	2.4849066	-2.40189261
40	2.4849066	-2.40189261
41	2.4849066	-2.40189261
42	2.4849066	-2.40189261
43	2.5649494	-2.15495880
44	2.5649494	-2.15495880
45	2.7080502	-2.04766155
46	2.7080502	-2.04766155
47	2.7725887	-1.76695493
48	2.7725887	-1.76695493
49	2.7725887	-1.76695493
50	2.8332133	-1.60696952
51	2.8332133	-1.60696952
52	2.9444390	-1.39480156
53	2.9444390	-1.39480156
54	2.9444390	-1.39480156
55	2.9444390	-1.39480156
56	2.9704145	-1.39480156
57	2.9957323	-1.32811414
58	2.9957323	-1.32811414
59	3.0445224	-1.26303986
60	3.0445224	-1.26303986
61	3.0910425	-1.07812882
62	3.0910425	-1.07812882
63	3.0910425	-1.07812882
64	3.0910425	-1.07812882
65	3.1354942	-1.01929150
66	3.1780538	-0.85167850
67	3.1780538	-0.85167850
68	3.1780538	-0.85167850

```
69   3.2188758 -0.64418353
70   3.2188758 -0.64418353
71   3.2188758 -0.64418353
72   3.2188758 -0.64418353
73   3.2580965 -0.40201964
74   3.2580965 -0.40201964
75   3.2580965 -0.40201964
76   3.2580965 -0.40201964
77   3.2580965 -0.40201964
78   3.2958369 -0.21665234
79   3.2958369 -0.21665234
80   3.2958369 -0.21665234
81   3.2958369 -0.21665234
82   3.3322045 -0.17100376
83   3.3322045 -0.17100376
84   3.3672958  0.01414288
85   3.3672958  0.01414288
86   3.3672958  0.01414288
87   3.3672958  0.01414288
88   3.4339872  0.15298854
89   3.4339872  0.15298854
90   3.4339872  0.15298854
91   3.4657359  0.29332420
92   3.4657359  0.29332420
93   3.4657359  0.29332420
94   3.4965076  0.53452625
95   3.4965076  0.53452625
96   3.4965076  0.53452625
97   3.4965076  0.53452625
98   3.4965076  0.53452625
99   3.5263605  0.68644312
100  3.5263605  0.68644312
101  3.5263605  0.68644312
102  3.5553481  0.79202783
103  3.5553481  0.79202783
104  3.5835189  1.01731522
105  3.5835189  1.01731522
106  3.5835189  1.01731522
107  3.5835189  1.01731522
108  3.6109179  1.13924325
109  3.6109179  1.13924325
110  3.6375862  1.26935338
111  3.6375862  1.26935338
112  3.6888795  1.33810246
113  3.6888795  1.33810246
114  3.7135721  1.57751462
115  3.7135721  1.57751462
116  3.7135721  1.57751462
117  3.7841896  1.66626400
118  3.8066625  1.76073683
119  3.8286414  1.86197307
120  3.8501476  1.97130859
121  3.8712010  2.09050046
122  3.8918203  2.36891658
```

```
123  3.8918203  2.36891658
124  3.9120230  2.53634755
125  3.9512437  2.96785557
126  3.9512437  2.96785557
127  3.9702919  3.68638461
128  3.9702919  3.68638461
129  4.0073332  4.39198515
130  4.0430513         Inf
```

\begin{center}\includegraphics{markdown_files/figure-latex/unnamed-chunk-4-3} \end{center}

```
[1] "Q-Q plot for loglogistic done"
```

Hazard Plots for Regression Covariates - Regression Time Interval Identification

Hazard curves stratified by group for each regression covariate are provided below, with the three time

\begin{center}\includegraphics{markdown_files/figure-latex/unnamed-chunk-5-1} \end{center}

\begin{center}\includegraphics{markdown_files/figure-latex/unnamed-chunk-5-2} \end{center}

\begin{center}\includegraphics{markdown_files/figure-latex/unnamed-chunk-5-3} \end{center}

\begin{center}\includegraphics{markdown_files/figure-latex/unnamed-chunk-5-4} \end{center}

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Regression Model Diagnostics

Cox-Snell residual plot for assessment of overall model fit and dfbeta residual plots for evaluation of

\begin{center}\includegraphics{markdown_files/figure-latex/unnamed-chunk-6-1} \end{center}

\begin{center}\includegraphics{markdown_files/figure-latex/unnamed-chunk-6-2} \end{center}

Warning in status - mod3$residuals: longer object length is not a multiple of shorter object length

\begin{center}\includegraphics{markdown_files/figure-latex/unnamed-chunk-6-3} \end{center}

\begin{center}\includegraphics{markdown_files/figure-latex/unnamed-chunk-6-4} \end{center}

\begin{center}\includegraphics{markdown_files/figure-latex/unnamed-chunk-6-5} \end{center}

\begin{center}\includegraphics{markdown_files/figure-latex/unnamed-chunk-6-6} \end{center}

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R Code

```r
knitr::opts_chunk$set(echo = TRUE)
knitr::opts_chunk$set(fig.height=4.5, fig.width=7)

library(readxl)
library(knitr)
library(tidyverse)
library(dplyr)
library(kableExtra)
library(survival)
library(survminer)
library(ggplot2)
library(VIM)
library(missForest)
library(ggplot2)
library(ggpubr)
library(MASS)
library(SurvCorr)
library(broom)

df = data.frame(read_excel("df.xlsx"))
df[df=="?"] = " "

df.new = data.frame(read_excel("df.new.xlsx"))

s.df = Surv(df.new$Survival,df.new$Status)

Indicator = c("0","1")
Age = c("< 63 Years", "\u2265 63 Years")
Effusion = c("Fluid is absent", "Fluid is present")
WMS = c("< 11", " \u2265 11")
FS = c("< 0.2"," \u2265 0.2")

groupings = data.frame(Indicator, Age, Effusion, WMS, FS)
```

```
kable(groupings, caption="Stratification Groupings", align="c") %>%
  kable_styling(position = "center", latex_options="hold_position")


missing.data = aggr(df) #visualize the missing information

set.seed(7522)
df.i = missForest(df, maxiter = 30, ntree = 1000)

round_df <- function(x, digits) {
  # round all numeric variables
  # x: data frame
  # digits: number of digits to round
  numeric_columns <- sapply(x, mode) == 'numeric'
  x[numeric_columns] <-  round(x[numeric_columns], digits)
  x}

df.impute = round_df(df.i$ximp,2) #imputed values table
df.new = df.impute[,c(-5,-12)] #remove incomplete strata from original data
Age.s = ifelse(df.impute$Age < 63,0,1) #new age strata based on imputed data #new age strata based on i
WMS.s = ifelse(df.impute$WMS < 14,0,1) #new WMS strata based on imputed data
Fshort.s = ifelse(df.impute$F.Shortening < 0.2,0,1) #new fshort strata based on imputed data
LVDD.s = ifelse(df.impute$LVDD < 4.75,0,1) #new lvdd strata based on imputed data
EPSS.s = ifelse(df.impute$EPSS < 11.1,0,1)#new epss strata based on imputed data


df.new$Age.s = Age.s
df.new$WMS.s = WMS.s
df.new$F.Short.s = Fshort.s
df.new$LVDD.s = LVDD.s
df.new$EPSS.s = EPSS.s

km.all = survfit(s.df~1,type="kaplan-meier", data=df.new)
km.allp = ggsurvplot(km.all,
                           palette = "#2E9FDF",
                           conf.int = TRUE,
                           title="Post-Myocardial Infarction Survival",
                           font.title=c(14,"bold.italic"),
                           font.subtitle = c(10,"italic"),
                           font.x = c(9, "bold.italic"),
                           font.y = c(9, "bold.italic"),
                           ylab="Surival Proportion",
                           xlab="Time to Death (Months)",
                           surv.median.line = "hv",
                           legend.title = "Groups",
                           legend.labs = "All")
km.allp

ks1 = data.frame(t(summary(km.all)$table))
ks1 = ks1[,c(1,4,5,7,8,9)]
colnames(ks1) = c("Records","Events","Mean","Median","Median 0.95 LCL","Median 0.95 UCL")
rownames(ks1) = c("All Groups")

kable(ks1, caption="Kaplan-Meier Estimates for All Groups",align="c", digits=2) %>%
```

```
  kable_styling(position = "center", latex_options="hold_position")
haz.all = ggsurvplot(km.all,
           fun = "cumhaz",
           palette = "#2E9FDF",
           conf.int = TRUE,
           title="Post-Myocardial Infarction Hazard",
           font.title=c(14,"bold.italic"),
           font.subtitle = c(10,"italic"),
           font.x = c(9, "bold.italic"),
           font.y = c(9, "bold.italic"),
           ylab="Cumulative Hazard",
           xlab="Time to Death (Months)",
           legend.title = "Groups",
           legend.labs = "All")

haz.all
km.p1 = list()

km.age = survfit(s.df~Age.s, type="kaplan-meier", data = df.new)
km.p1[[1]] = ggsurvplot(km.age,
                           palette = c("darkcyan","darkgoldenrod3","darkorange3"),
                           subtitle="Survival, Stratified by Age Group",
                           font.subtitle = c(10,"italic"),
                           font.x = c(9, "bold.italic"),
                           font.y = c(9, "bold.italic"),
                           ylab="Surival Proportion",
                           xlab="Time to Death (Months)",
                           surv.median.line = "hv",
                           legend.title = "Groups",
                           legend.labs = c("< 63 Years","\u2265 63 Years"))

km.effusion = survfit(s.df~P.Effusion, type="kaplan-meier", data = df.new)
km.p1[[2]] = ggsurvplot(km.effusion,
                           palette = c("darkcyan","darkgoldenrod3"),
                           subtitle="Survival, Stratified by Presence of Pericardial Effusion",
                           font.subtitle = c(10,"italic"),
                           font.x = c(9, "bold.italic"),
                           font.y = c(9, "bold.italic"),
                           ylab="Surival Proportion",
                           xlab="Time to Death (Months)",
                           surv.median.line = "hv",
                           legend.title = "Groups",
                           legend.labs = c("Present","Absent"))

arrange_ggsurvplots(km.p1, print=TRUE, ncol=2, nrow=1)
ks2 = data.frame(summary(km.age)$table)
ks3 = data.frame(summary(km.effusion)$table)

ks2.3 = rbind(ks2, ks3)
ks2.3 = ks2.3[,c(1,4,5,7,8,9)]
colnames(ks2.3) = c("Records","Events","Mean","Median","Median 0.95 LCL","Median 0.95 UCL")
rownames(ks2.3) = c("Age < 63", "Age \u2265 63","Absent","Present")

kable(ks2.3, caption="Kaplan-Meier Estimates Stratified by Age and Pericardial Effusion Presence",align=
```

```
  kable_styling(position = "center", latex_options="hold_position")

km.agediff = survdiff(s.df~Age.s, data = df.new)
km.effusiondiff = survdiff(s.df~P.Effusion, data = df.new)

ks2.diff = data.frame(tidy(km.agediff))
ks3.diff = data.frame(tidy(km.effusiondiff))

ks2.diff = ks2.diff[,c(2,3,4)]
ks3.diff = ks3.diff[,c(2,3,4)]
ks2.3diff = rbind(ks2.diff,ks3.diff)
colnames(ks2.3diff) = c("N","Observed","Expected")
rownames(ks2.3diff) = c("Age < 63", "Age \u2265 63","Absent","Present")

kable(ks2.3diff, caption = "Summary of Differences Between Strata")

haz.p1 = list()

haz.p1[[1]] = ggsurvplot(km.age,
           fun = "cumhaz",
           palette = c("darkcyan","darkgoldenrod3"),
           title="Cumulative Hazard, Stratified by Age Group",
           font.title = c(10,"bold.italic"),
           font.x = c(9, "bold.italic"),
           font.y = c(9, "bold.italic"),
           ylab="Cumulative Hazard",
           xlab="Time to Death (Months)",
           legend.title = "Groups",
           legend.labs = c("< 63 Year","\u2265 63 Years"))

haz.p1[[2]] = ggsurvplot(km.effusion,
           fun = "cumhaz",
           palette = c("darkcyan","darkgoldenrod3"),
           title="Cumulative Hazard, Stratified by Pericardial Effusion Presence",
           font.title = c(10,"bold.italic"),
           font.x = c(9, "bold.italic"),
           font.y = c(9, "bold.italic"),
           ylab="Cumulative Hazard",
           xlab="Time to Death (Months)",
           legend.title = "Groups",
           legend.labs = c("Present","Absent"))

arrange_ggsurvplots(haz.p1, print=TRUE, ncol=2, nrow=1)
km.p2 = list()

km.wms = survfit(s.df~WMS.s, type="kaplan-meier", data = df.new)
km.p2[[1]] = ggsurvplot(km.wms,
                           palette = c("darkcyan","darkgoldenrod3","darkorange3"),
                           subtitle="Survival, Stratified by Wall Motion Score",
                           font.subtitle = c(10,"italic"),
                           font.x = c(9, "bold.italic"),
                           font.y = c(9, "bold.italic"),
                           ylab="Surival Proportion",
                           xlab="Time to Death (Months)",
```

```
                            surv.median.line = "hv",
                            legend.title = "Groups",
                            legend.labs = c("< 14","\u2265 14"))

km.fshort = survfit(s.df~Fshort.s, type="kaplan-meier", data = df.new)
km.p2[[2]] = ggsurvplot(km.fshort,
                            palette = c("darkcyan","darkgoldenrod3"),
                            subtitle="Survival, Stratified by fractional Shortening",
                            font.subtitle = c(10,"italic"),
                            font.x = c(9, "bold.italic"),
                            font.y = c(9, "bold.italic"),
                            ylab="Surival Proportion",
                            xlab="Time to Death (Months)",
                            surv.median.line = "hv",
                            legend.title = "Groups",
                            legend.labs = c("< 0.2","\u2265 0.2"))

arrange_ggsurvplots(km.p2, print=TRUE, ncol=2, nrow=1)
ks4 = data.frame(summary(km.wms)$table)
ks5 = data.frame(summary(km.fshort)$table)

ks4.5 = rbind(ks4, ks5)
ks4.5 = ks4.5[,c(1,4,5,7,8,9)]
colnames(ks4.5) = c("Records","Events","Mean","Median","Median 0.95 LCL","Median 0.95 UCL")
rownames(ks4.5) = c("Score < 14", "Score \u2265 14","Length < 0.2", "Length \u2265 0.2")

kable(ks4.5, caption="Kaplan-Meier Estimates Stratified by Wall Motion Score and fractional Shortening"
  kable_styling(position = "center", latex_options="hold_position")

km.wmsdiff = survdiff(s.df~WMS.s, data = df.new)
km.f.shortdiff = survdiff(s.df~Fshort.s, data = df.new)

ks4.diff = data.frame(tidy(km.wmsdiff))
ks5.diff = data.frame(tidy(km.f.shortdiff))

ks4.diff = ks4.diff[,c(2,3,4)]
ks5.diff = ks5.diff[,c(2,3,4)]
ks4.5diff = rbind(ks4.diff,ks5.diff)
colnames(ks4.5diff) = c("N","Observed","Expected")
rownames(ks4.5diff) = c("Wall Motion Score < 14", "Wall Motion Score \u2265 14","Fractional Shortening


kable(ks4.5diff, caption = "Summary of Differences Between Strata")

haz.p2 = list()

haz.p2[[1]] = ggsurvplot(km.wms,
           fun = "cumhaz",
           palette = c("darkcyan","darkgoldenrod3"),
           title="Cumulative Hazard, Stratified by Wall Motion Score",
           font.title = c(10,"bold.italic"),
           font.x = c(9, "bold.italic"),
           font.y = c(9, "bold.italic"),
           ylab="Cumulative Hazard",
```

```
            xlab="Time to Death (Months)",
            legend.title = "Groups",
            legend.labs = c("< 14","\u2265 14"))

haz.p2[[2]] = ggsurvplot(km.fshort,
            fun = "cumhaz",
            palette = c("darkcyan","darkgoldenrod3"),
            title="Cumulative Hazard, Stratified by fractional Shortening",
            font.title = c(10,"bold.italic"),
            font.x = c(9, "bold.italic"),
            font.y = c(9, "bold.italic"),
            ylab="Cumulative Hazard",
            xlab="Time to Death (Months)",
            legend.title = "Groups",
            legend.labs = c("< 0.2","\u2265 0.2"))

arrange_ggsurvplots(haz.p2, print=TRUE, ncol=2, nrow=1)


months=df.new$Survival
status=df.new$Status
months.u=months[status == 1]
months.u = sort(months.u)
nu = length(months.u)

#Weibull model plot

weib.fit=survreg(Surv(months,status)~1,dist="weib")
alphahat=1/weib.fit$scale
scalehat=exp(weib.fit$coefficients)
Shat.w = 1- pweibull(months.u,alphahat,scalehat)
plot(km.all,conf.int=F,xlab="time until death (in months)",
     ylab="proportion survived",
     main= "Survival Curves - Weibull and Kaplan-Meier",
     lwd=2,
     col = "darkcyan")
lines(months.u, Shat.w, col="darkgoldenrod3",lwd=2)
legend(40, 0.8, legend=c("Kaplan-Meier", "Weibull"),
       col=c("darkcyan","darkgoldenrod3"), lty=1:1, cex=0.8,lwd=2)
abline(h=0)

#log-normal model plot

lognorm.fit=survreg(Surv(months,status)~1,dist="lognormal")
muhat=lognorm.fit$coefficients
sigmahat=lognorm.fit$scale
Shat.l = 1- pnorm(log(months.u),muhat,sigmahat)
plot(km.all,conf.int=F,xlab="time until death (in months)",
     ylab="proportion survived",
     main="Survival Curves - Log-normal and Kaplan-Meier",
     lwd=2,
     col="darkcyan")
lines(months.u, Shat.l, col="darkgoldenrod3",lwd=2)
legend(40, 0.8, legend=c("Kaplain", "Weibull"), lwd=2,
```

```
       col=c("darkcyan","darkgoldenrod3"), lty=1:1, cex=0.8)
abline(h=0)

#log-logistic model plot

loglog.fit=survreg(Surv(months,status)~1,dist="loglogistic")
muhat=loglog.fit$coefficients
sigmahat=loglog.fit$scale
Shat.ll = 1- plogis(log(months.u),muhat,sigmahat)
plot(km.all,conf.int=F,xlab="time until death (in months)",
     ylab="proportion survived",
     main="Survival Curves - Log-logistic and Kaplan-Meier",
     lwd=2,
     col="darkcyan")
lines(months.u, Shat.ll, col="darkgoldenrod3",lwd=2,)
legend(40, 0.8, legend=c("Kaplan", "Weibull"), lwd=2,
       col=c("darkcyan","darkgoldenrod3"), lty=1:1, cex=0.8)
abline(h=0)


param.est = data.frame(read_excel("param.est.xlsx"))
kable(param.est,
      col.names = c("Model","Quantile", "Point Estimate", "95% LCL", "95% UCL", "Interval Length")
      )


library("gtsummary")
LL=0.0
UL=26.0

#Subset the data based on the time region

months=df.new$Survival[df.new$Survival>=LL & df.new$Survival<=UL]
status=df.new$Status[df.new$Survival>=LL & df.new$Survival<=UL]
Age=df.new$Age[df.new$Survival>=LL & df.new$Survival<=UL]
Pericardial_Effusion=df.new$P.Effusion[df.new$Survival>=LL & df.new$Survival<=UL]
Wall_Motion_Score=df.new$WMS[df.new$Survival>=LL & df.new$Survival<=UL]
Fractional_Shortening=df.new$F.Shortening[df.new$Survival>=LL & df.new$Survival<=UL]

#Create initial model fit

cph.fit1=coxph(Surv(months,status)~Age+Pericardial_Effusion+Wall_Motion_Score+Fractional_Shortening,x=T

#Reduce with StepAIC procedure

cph.fit2=stepAIC(cph.fit1,~.^2,direction="both",trace=FALSE)
mod1=cph.fit2

t1 <-
  mod1 %>%
  tbl_regression(exponentiate = TRUE)%>%
  add_nevent()

LL=26
```

```
UL=46

#Subset the data based on the time region

months=df.new$Survival[df.new$Survival>LL & df.new$Survival<=UL]
status=df.new$Status[df.new$Survival>LL & df.new$Survival<=UL]
Age=df.new$Age[df.new$Survival>LL & df.new$Survival<=UL]
Pericardial_Effusion=df.new$P.Effusion[df.new$Survival>LL & df.new$Survival<=UL]
Wall_Motion_Score=df.new$WMS[df.new$Survival>LL & df.new$Survival<=UL]
Fractional_Shortening=df.new$F.Shortening[df.new$Survival>LL & df.new$Survival<=UL]

#Create initial model fit

cph.fit1=coxph(Surv(months,status)~Age+Pericardial_Effusion+Wall_Motion_Score+Fractional_Shortening,x=T)

#Reduce with StepAIC procedure

cph.fit2=stepAIC(cph.fit1,~.^2,direction="both",trace=FALSE)
mod2=cph.fit2

t2 <-
  mod2 %>%
  tbl_regression(exponentiate = TRUE) %>%
  add_nevent()

#Subset the data based on the time region

months=df.new$Survival[df.new$Survival>UL]
status=df.new$Status[df.new$Survival>UL]
Age=df.new$Age[df.new$Survival>UL]
Pericardial_Effusion=df.new$P.Effusion[df.new$Survival>UL]
Wall_Motion_Score=df.new$WMS[df.new$Survival>UL]
Fractional_Shortening=df.new$F.Shortening[df.new$Survival>UL]

#Create initial model fit

cph.fit1=coxph(Surv(months,status)~Age+Pericardial_Effusion+Wall_Motion_Score+Fractional_Shortening,x=T)

#Reduce with StepAIC procedure

cph.fit2=stepAIC(cph.fit1,~.^2,direction="backward",trace=FALSE)
mod3=cph.fit2

t3 <-
  mod3 %>%
  tbl_regression(exponentiate = TRUE)%>%
  add_nevent()

# merge tables

  tbl_merge(
    tbls = list(t1, t2, t3),
    tab_spanner = c("Model 1", "Model 2", "Model 3")
  )
```

```
df.sum = data.frame(read_excel("df.sum.xlsx"))

kable(df.sum, "latex",
      booktabs = TRUE,
      longtable = TRUE,
      linesep = "\\addlinespace",
      caption = "Summary of Dataset Covariates") %>%
  kable_styling(latex_options = c("hold_position","repeat_header"),
                full_width = TRUE)


kable(df, "latex",
      booktabs = TRUE,
      longtable = TRUE,
      caption = "Original Dataset") %>%
  kable_styling(latex_options = c("hold_position","repeat_header"),
                full_width = TRUE)
kable(df.new, "latex",
      booktabs = TRUE,
      longtable = TRUE,
      caption = "Imputed Dataset") %>%
  kable_styling(latex_options = c("hold_position","repeat_header"),
                full_width = TRUE)


km.sum = data.frame(km.all$n.risk, km.all$n.event, km.all$n.censor, km.all$surv, km.all$std.err, km.all$

kable(km.sum,
      caption="Kaplan-Meier Estimate Summary",
      col.names = c("Ni","Di","Ci","Survival","Std. Err", "95% LCL", "95% UCL")) %>%
  kable_styling(latex_options = "hold_position")

#Q-Q Plots - Weibull, Log-lognormal, Log-logistic
#qq.surv function:
#Author: Jong Sung Kim, Date: 8/10/2004
# Edited by D. Leif Rustvold, Date: 6/7/2006

qq.surv <- function(time, status, pdgy = 0, distribution = "weibull", scale = 0, adjpb =
                      0.025, ...)
{
  ## Purpose: qqplot for distributions that satisfy a log-linear form
  ## for one sample.  It fits each sample with own intercept and slope
  ## (location and scale).
  ##----------------------------------------------------------------------
  ## Arguments
  ## =========
  ## time:   observed time
  ## status: censoring indicator
  ##
  ## Options
  ## =======
  ## pdgy:   Flag to generate for pedagogical purposes additional lines
  ##         incorporating the effect of how we treat censored
```

```
##         observations on the MLE's (equivalently estimated line).
##         pdgy=0 is the default, for no additional lines.
##         pdgy=1 generates additional lines.
## distribution:  Distribution for fit.
##         May take values "weibull", "loglogistic", or "lognormal".
##         The default is "weibull" distribution (exponential model with
##         scale=1).  Enter "loglogistic" to fit loglogistic distribution;
##         Enter "lognormal" to fit lognormal distribution.
## scale:  Scale parameter.  scale=0 is the default. This estimates
##         the scale. With distribution "weibull", scale=1 fits the
##         exponential model.
## adjpb:  Replaces the zero survival probability when the max is exact.
##         Or when the min is censored, it replaces the survival
##         probability by 1 - adjpb.  Default is 0.025.
##         This has nothing to do with the MLE line, but is solely for
##         plotting the point on the graph.
##-------------------------------------------------------------------
## Author: Jong Sung Kim, Date: 8/10/2004
## Edited by D. Leif Rustvold, Date: 6/7/2006
d <- data.frame(time, status)
# data frame
d <- na.exclude(d)
# Missing observations excluded
d <- d[order(d$time),  ]
# Rearranging the observed times into a nondecreasing order
# Unordered times sometimes mess up QQ-plots.
time <- d$time
# sorted time
status <- d$status
# status corresponding to sorted time
data <- Surv(time, status)
# Surv object
t.c <- class(data)
if((!is.null(t.c)) && t.c == "Surv")
  data <- list(data)
t.s <- summary(survfit(Surv(time, status)~1, type = "kaplan-meier",
                       na.action = na.exclude))
survp <- t.s$surv
survtime <- t.s$time
rare <- F
# rare = T indicates that the smallest observation is censored
if(time[1] < survtime[1]) {
  print("Smallest observation is censored!")
  survp <- c(1 - adjpb, survp)
  survtime <- c(time[1], survtime)
  rare <- T
}
#############
#############
xlabs <- ifelse(distribution == "weibull",
                "Standard Extreme Value Quantiles", ifelse(distribution ==
                                                             "loglogistic", "Standard Log-logistic Qua
                                                               distribution == "lognormal", "Standard
                                                               "")))
```

```
if(pdgy == 1) {
  ###############
  t.s.exactall <- summary(survfit(Surv(time, status >= 0)~1, type
                                  = "kaplan-meier", na.action = na.exclude))
  exactall.survp <- t.s.exactall$surv
  exactall.survtime <- t.s.exactall$time
  exactall.length <- length(exactall.survtime)
  exactall.survp[exactall.length] <- adjpb
  t.ss.exactall <- exactall.survp
  #quant.exactall <- qweibull(1 - t.ss.exactall, 1)
  quant.exactall <- switch(distribution,
                           weibull = qweibull(1 - t.ss.exactall, 1),
                           lognormal = qlnorm(1 - t.ss.exactall),
                           loglogistic = exp(logis((1 - t.ss.exactall))))
  exactall.sevq <- log(quant.exactall)
  # standard extreme value quantile
  exactall.logtime <- log(exactall.survtime)
  print(data.frame(exactall.logtime, exactall.sevq))
  ###############
  ok <- status == 1
  t.s.exact <- summary(survfit(Surv(time[ok], status[ok])~1, type
                               = "kaplan-meier", na.action = na.exclude))
  exact.survp <- t.s.exact$surv
  exact.survtime <- t.s.exact$time
  exact.length <- length(exact.survtime)
  exact.survp[exact.length] <- adjpb
  t.ss.exact <- exact.survp
  #quant.exact <- qweibull(1 - t.ss.exact, 1)
  quant.exact <- switch(distribution,
                        weibull = qweibull(1 - t.ss.exact, 1),
                        lognormal = qlnorm(1 - t.ss.exact),
                        loglogistic = exp(qlogis(1 - t.ss.exact)))
  exact.sevq <- log(quant.exact)
  # standard extreme value quantile
  exact.logtime <- log(exact.survtime)
  print(data.frame(exact.logtime, exact.sevq))
  ###############
  n <- length(time)
  t.ss <- rep(0, n)
  for(i in 1:n) {
    # This loop assigns probabilities to censored time points,
    # and takes care of tied observations as well
    idx <- time[i] >= survtime
    t.ss[i] <- min(survp[idx], na.rm = T)
  }
  #sevq <- log(qweibull(1 - t.ss, 1))
  sevq <- log(switch(distribution,
                     weibull = qweibull(1 - t.ss, 1),
                     lognormal = qlnorm(1 - t.ss),
                     loglogistic = exp(qlogis(1 - t.ss))))
  # standard extreme value quantile
  logtime <- log(time)
  print(data.frame(logtime, sevq))
  ######## Multiple Plot starts ##########
```

```
  xrange <- range(c(exactall.sevq, exact.sevq, sevq))
  yrange <- range(c(exactall.logtime, exact.logtime, logtime))
  par(mar = c(5, 5, 2, 2))
  plot(sevq, logtime, type = "n", lty = 1, xlim = xrange, ylim
       = yrange, xlab = xlabs, ylab = "Ordered Log Time",
       ...)
  points(sevq[ok], logtime[ok], pch = 1)
  # exact points portion
  points(sevq[!ok], logtime[!ok], pch = "\255", font = 8)
  # censored points portion
  points(exactall.sevq, exactall.logtime, pch = 3, col = 6)
  # exactall
  exactallfit <- survreg(Surv(time, status >= 0) ~ 1, dist =
                           distribution, scale = scale)
  # treating censored as exac
  t
  abline(exactallfit$coef, exactallfit$scale, lty = 3, col = 6)
  points(exact.sevq, exact.logtime, pch = 5, col = 5)
  # exact points only
  exactonlyfit <- survreg(Surv(time[ok], status[ok]) ~ 1, dist
                          = distribution, scale = scale)
  # deleting censored
  abline(exactonlyfit$coef, exactonlyfit$scale, lty = 2, col = 5
  )
  fit <- survreg(Surv(time, status) ~ 1, dist = "weibull", scale
                 = scale)
  # censoring taken into account
  abline(fit$coef, fit$scale, lty = 1, col = 1)
}
else {
  n <- length(time)
  t.ss <- rep(0, n)
  for(i in 1:n) {
    # This loop assigns probabilities to censored time points,
    # and takes care of tied observations as well
    idx <- time[i] >= survtime
    t.ss[i] <- min(survp[idx], na.rm = T)
  }
  #sevq <- log(qweibull(1 - t.ss, 1))
  sevq <- log(switch(distribution,
                     weibull = qweibull(1 - t.ss, 1),
                     lognormal = qlnorm(1 - t.ss),
                     loglogistic = exp(qlogis(1 - t.ss))))
  # standard extreme value quantile
  logtime <- log(time)
  print(data.frame(logtime, sevq))
  par(mar = c(5, 5, 2, 2))
  plot(sevq, logtime, type = "n", xlab = xlabs, ylab =
         "Ordered Log Time", ...)
  ok <- status == 1
  # exact status only
  points(sevq[ok], logtime[ok], pch = 1)
  # exact points only
  points(sevq[!ok], logtime[!ok], pch = "\255", font = 8)
```

```
    # censored points only
    fit <- survreg(Surv(time, status) ~ 1, dist = distribution,
                   scale = scale)
    # censoring taken into account
    abline(fit$coef, fit$scale, lty = 1, col = 1)
  }
  ymax <- max(logtime)
  yrange <- diff(range(logtime))
  yn <- ymax - yrange * seq(0, by = 0.05, length = 5)
  if(pdgy == 1) {
    xmin <- min(c(sevq, exact.sevq, exactall.sevq))
    xrange <- diff(range(c(sevq, exact.sevq, exactall.sevq)))
  }
  else {
    xmin <- min(sevq)
    xrange <- diff(range(sevq))
  }
  x1 <- xmin + 0.05 * xrange
  x2 <- xmin + 0.1 * xrange
  x3 <- xmin + 0.15 * xrange
  points(x1, yn[1], pch = "\255", font = 8)
  text(x3, yn[1], "censored", adj = 0)
  points(x1, yn[2], pch = 1)
  text(x3, yn[2], "exact", adj = 0)
  if(pdgy == 1) {
    lines(c(x1, x2), rep(yn[3], 2), lty = 1, col = 1, lwd = 3)
    text(x3, yn[3], "censoring taken into account", adj = 0)
    lines(c(x1, x2), rep(yn[4], 2), lty = 3, col = 6, lwd = 3)
    text(x3, yn[4], "treating censored as exact", adj = 0)
    lines(c(x1, x2), rep(yn[5], 2), lty = 2, col = 5, lwd = 3)
    text(x3, yn[5], "deleting censored", adj = 0)
  }
  on.exit()
  paste("Q-Q plot for", distribution, "done")
}

months=df.new$Survival
status=df.new$Status
qq.surv(months, status, distribution = "weibull",
        adjpb=0,
        main="Q-Q plot - Weibull fit")
qq.surv(months, status, distribution = "lognormal",
        adjpb=0,
        main="Q-Q plot - Log-normal fit")
qq.surv(months, status, distribution = "loglogistic",
        adjpb=0,
        main="Q-Q plot - Log-logistic fit")


p= ggsurvplot(km.age,
              fun = "cumhaz",
              palette = c("darkcyan","darkgoldenrod3","darkorange3"),
              subtitle="Hazard, Stratified by Age Group",
              font.subtitle = c(10,"italic"),
```

```
              font.x = c(9, "bold.italic"),
              font.y = c(9, "bold.italic"),
              ylab="Surival Proportion",
              xlab="Time to Death (Months)",
              legend.title = "Groups",
              legend.labs = c("Age < 63","Age => 63")
)
p$plot + geom_vline(xintercept=26)+
  geom_vline(xintercept=46)

p = ggsurvplot(km.effusion,
               fun = "cumhaz",
               palette = c("darkcyan","darkgoldenrod3"),
               subtitle="Hazard, Stratified by Pericardial Effusion Presence",
               font.subtitle = c(10,"italic"),
               font.x = c(9, "bold.italic"),
               font.y = c(9, "bold.italic"),
               ylab="Surival Proportion",
               xlab="Time to Death (Months)",
               legend.title = "Groups",
               legend.labs = c("Present","Absent"))
p$plot + geom_vline(xintercept=26)+
  geom_vline(xintercept=46)

p = ggsurvplot(km.wms,
               fun = "cumhaz",
               palette = c("darkcyan","darkgoldenrod3","darkorange3"),
               subtitle="Hazard, Stratified by Wall Motion Index",
               font.subtitle = c(10,"italic"),
               font.x = c(9, "bold.italic"),
               font.y = c(9, "bold.italic"),
               ylab="Surival Proportion",
               xlab="Time to Death (Months)")
p$plot + geom_vline(xintercept=26)+
  geom_vline(xintercept=46)


p = ggsurvplot(km.fshort,
               fun = "cumhaz",
               palette = c("darkcyan","darkgoldenrod3","darkorange3"),
               subtitle="Hazard, Stratified by Fractional Shortening",
               font.subtitle = c(10,"italic"),
               font.x = c(9, "bold.italic"),
               font.y = c(9, "bold.italic"),
               ylab="Surival Proportion",
               xlab="Time to Death (Months)"
)
p$plot + geom_vline(xintercept=26)+
  geom_vline(xintercept=46)

#Cox-Snell residual analysis for overall model fit

status=df.new$Status[df.new$Survival>=0 & df.new$Survival<=26]
rc=abs(status - mod1$residuals)
```

```
km.rc = survfit(Surv(rc,status)~1)
summary.km.rc=summary(km.rc)
rcu=summary.km.rc$time
surv.rc = summary.km.rc$surv
plot(rcu,-log(surv.rc),type="p",
     xlab="Cox-Snell residual rc",ylab="Cumulative hazard on rc",
     main="Model 1 - Cox-Snell residual model fit evaluation")
abline(a=0,b=1); abline(v=0); abline(h=0)

status=df.new$Status[df.new$Survival>26 & df.new$Survival<=46]
rc=abs(status - mod2$residuals)
km.rc = survfit(Surv(rc,status)~1)
summary.km.rc=summary(km.rc)
rcu=summary.km.rc$time
surv.rc = summary.km.rc$surv
plot(rcu,-log(surv.rc),type="p",
     xlab="Cox-Snell residual rc",ylab="Cumulative hazard on rc",
     main="Model 2 - Cox-Snell residual model fit evaluation")
abline(a=0,b=1); abline(v=0); abline(h=0)

months=df.new$Survival[df.new$Survival>46]
rc=abs(status - mod3$residuals)
km.rc = survfit(Surv(rc,status)~1)
summary.km.rc=summary(km.rc)
rcu=summary.km.rc$time
surv.rc = summary.km.rc$surv
plot(rcu,-log(surv.rc),type="p",
     xlab="Cox-Snell residual rc",ylab="Cumulative hazard on rc",
     main="Model 3 - Cox-Snell residual model fit evaluation")
abline(a=0,b=1); abline(v=0); abline(h=0)

#Schoenfeld residuals; test for constant coefficients

test.ph <- cox.zph(mod1)
ggcoxzph(test.ph, main="Schoenfeld Residuals - Const Coeff Evaluation for Model 1")

test.ph <- cox.zph(mod2)
ggcoxzph(test.ph, main="Schoenfeld Residuals - Const Coeff Evaluation for Model 2")

test.ph <- cox.zph(mod3)
ggcoxzph(test.ph, main="Schoenfeld Residuals - Const Coeff Evaluation for Model 3")
```