American Journal of Health Research
2023; 11(5): 130-139
http://www.sciencepublishinggroup.com/j/ajhr
doi: 10.11648/j.ajhr.20231105.11
ISSN: 2330-8788 (Print); ISSN: 2330-8796 (Online)

Survival Analysis of Coronary Heart Disease Patient During Revascularization of Coronary Artery in Case of Debre Birehan Compressive Specialized Hospital

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To cite this article:

Dagne Tesfaye Mengistie, Buzuneh Tasfa Marine. Survival Analysis of Coronary Heart Disease Patient During Revascularization of Coronary Artery in Case of Debre Birehan Compressive Specialized Hospital. *American Journal of Health Research*. Vol. 11, No. 5, 2023, pp. 130-139. doi: 10.11648/j.ajhr.20231105.11

Received: July 22, 2023; **Accepted**: September 5, 2023; **Published**: September 25, 2023

Abstract: *Introduction*: Coronary artery disease (CAD) is one manifestation of ischemic heart disease, which is the leading cause of mortality in the world. Objective: The core objective of this investigation was to analyze Survival Analysis of coronary heart disease of patient during revascularization coronary artery performed. *Method*: The study was constructed on the data which have 250 patients (subject) with 6 independent variables. The study more explored using survival models such as semi-parametric (Cox PH model) and parametric models (Accelerated Failure Time). Because of some assumptions of cox PH do not well fitted. As we know from theoretical knowledge even if the assumptions are many the parametric models has better acceptance. Basically the data source is already given from Debre Berehan Compressive specialized hospital in registry patient of acute coronary event. *Result*: According to the results of this study the death of coronary heart patient is affected by factors such as age of patients, revascularization performs, and the day of hospital stays. The hazard ratio for two groups is proportional throughout the days (time) as shown by this paper. The proportion of the death of patient which revascularization performed less than that of did not revascularization of coronary artery performed. And also from AFT model of Weibull the patient of didn't use revascularization is more accelerate to death then patient use revascularization method.

Keywords: Coronary Heart Disease, Accelerated Failure Time, St-Segment Deviation, Revascularization of Coronary Artery

1. Introduction

1.1. Background of Study

Coronary heart disease (CHD), also recognized as coronary artery disease (CAD), is instigated by the buildup of plaque in the arteries that supply oxygen-rich blood to the heart. Plaque, a mixture of fat, cholesterol, and calcium deposits, can build up in the arteries over many years [1, 2]. Over time, this plaque can origin the narrowing and hardening of the coronary arteries, a condition called atherosclerosis. Coronary heart disease (CHD) is the leading basis of death world-wide [3]. Although men have higher rates than women at all ages, and coronary disease occurs up to 10 years later in wome [4], CHD is a main source of death for both sexes. Despite the fact that age-related mortality by CAD has been markedly concentrated through the last decennia, CAD, is one of the most important diseases of the 21st century, considering its morbidity and death [5]. Coronary Artery Disease (CAD) is the important cause of death globally where India has the highest burden. It causes 3 million deaths/ year, accounting for 25% of all mortality in India. Hospitals statistics reveal that 20-25% of all medical admissions are due to Coronary artery disease [6].

According to the National Commission on Macroeconomics and Health (NCMH), there would be around 62 million patients with CAD by 2015 in India, and of these, 23 million would be patients younger than 40 years of age. By 2020, 60% of the world's heart disease is expected to occur in India [7, 8]. The risk of CAD in

Indians is 3-4 times higher than white Americans, 6 times higher than Chinese and 20 times higher than Japanese [8]. Despite a recent decline in the developed countries, both CAD mortality and the prevalence of CAD risk factors continue to rise rapidly in the developing countries. Clearly, there is a need for concerned efforts directed at prevention and effective treatment of this epidemic one of the risk factor that so many patients die by coronary heart disease due to the absences of hear (artery) revascularization. Coronary artery bypass grafting (CABG) is one option to treat a patient with CAD. Myocardial ischemia is a rare but severe complication to CABG and myocardial ischemia is difficult to validate after CABG [9]. Coronary angiography is the golden standard to distinguish between graft-related and graft–unrelated ischemia. In this study there are a lot of factor which related to the coronary heart disease like age, coronary angiography, and systolic blood pressure. so identifying the factor that significant effect of coronary heart disease [10].

1.2. Statement of the Problem

CHD is the most collective cause of death in both men and women in the world. In patients with CHD, the majority survive their first experimental performance. In patients with symptomatic disease, morbidity and mortality is reduced through therapeutic and revascularization procedures and over the longer term by lifestyle changes, risk factor modification, and the use of prophylactic drug therapies [11]. When the acute appearances of coronary artery disease rapid cardiac death and acute myocardial infarction are considered together, then one in two patients with new or recurrent disease will have died within 30 days of their acute clinical presentation. About 69% die in the community, 29% die in hospital and the other 2% die within year [12].

1.3. Objectives

1.3.1. Main Objective

To analysis the survives of patient of coronary heart disease during revascularization of coronary artery performed.

1.3.2. Specific Objective

To determine the survive of patient before and after revascularization artery performed.

To determine important factors (covariates) associated with the survive of patient of coronary heart disease during revascularization performed.

To applies different survival model and identifies which one is the best and appropriate for this data.

1.4. Importance of the Study

The results of this study will improve the factor that associated with the coronary heart disease and the factor that affect the treatment of patient. Also to improve that the revascularization of coronary artery is the significant and important method to reduce the death of patient due to coronary heart disease to understand and practice of this survival data on different software like SAS, R, SPSS, STATA and identified the properties of survival data, different survival model (parametric, non-parametric and semi-parametric method). From parametric method concentrated on Accelerated Failure Time like, exponential, gamma, Weibull model. In non-parametric planner Meier, lifetable and nelson method are identified which is best method for this data [13, 14].

2. Data and Material

2.1. Foundation of Data and Study Variables

This study was applied on a secondary data with a sample of 250 of patient with coronary heart disease during revascularization of coronary artery performed for treatment that which provided from Debre Berehan specialized hospital in registry patient of acute coronary event.

2.2. Study Variable

Response (dependent) variable

Days (time) to death during follow up

Explanatory/independent variable

1. age
2. systolic blood pressure
3. ST-segment deviation
4. Length of hospital stay
5. Day to revascularization perform

Table 1. *Description of independent variables used in the analysis.*

Variable Name	Codes/Values
Follow Up Time	0.5* - 180 days
Death During Follow Up	1= Death, 0 = Censored
Revascularization Performed	1 = Yes, 0 = No
Days to Revascularization	0 - 14 if revasc=1 After Admission Same as days if revasc = 0
Length of Hospital Stay	Days
Age at Admission	Year
Systolic Blood Pressure	mm Hg
ST-segment deviation	1= Yes, 0=No

2.3. Survival Model and Method of Estimation

Survival Function S(t)

This function also called Survivorship Function and it captures the proportion of individuals for which the event of interest has not yet happened by time t [15]. The survival function, denoted by S(t), is defined as the probability that an individual survives longer than t:

$$S(t) = P \text{ (an individual survives longer than t)} = P(T > t)$$

By letting T be a continuous random variable with cumulative distribution function F(t) in the interval $[0, \infty)$.

From the definition of the cumulative distribution function F(t) of T,

$$S(t) = 1 - P \text{ (an individual fails before t)} = 1 - F(t)$$

Here S(t) is a non-increasing function of time t with the properties

$$S(t) = \begin{cases} 1\ for\ t = 1 \\ 0\ for\ t = \infty \end{cases}$$

Censoring:

Right censoring: a subject is right censored if it is known that failure occurs sometime after the recorded follow-up period.

Left censoring: a subject is left censored; it is known that the failure occurs some time before the recorded follow-up period.

Interval censoring: a subject is interval censored if it is known that the event occurs between two times, but the exact time of failure is not known. In effect we say 'I know that the event occurred between date A and date B: I know that the event occurred, but I don't know exactly when.

Hazard Rate λ(t)

The hazard function h(t) of survival time T gives the conditional failure rate. This is defined as the probability of failure during a very small time interval, assuming that the individual has survived to the beginning of the interval, or as the limit of the probability that an individual fails in a very short interval, t +Δt, given that the individual has survived to time t: [16]

$$h(t)=\lim_{\Delta t \to 0} \frac{p(an\ individual\ fails\ in\ interval(t, t+\Delta t) giventhe\ individual\ has\ survived\ to\ t}{\Delta t}$$

The hazard function can also be defined in terms of the cumulative distribution function F(t) and the probability density function f(t):

$$h(t) = \frac{f(t)}{1-f(t)}$$

The hazard function is also known as the instantaneous failure rate, force of mortality, conditional mortality rate, and age-specific failure rate [17]. Generally the survival function is most useful for comparing the survival progress of two or more strata whereas the hazard function gives a more useful description of the risk of failure at any time point.

Kaplan-Meier (KM) Estimator

The first step in the analysis of ungrouped censored survival data is normally to obtain the Kaplan-Meier estimate of the survivor function. To obtain the Kaplan-Meier estimate, a series of time intervals is constructed, as for the life-table estimate. However, each of these intervals is designed to be such that one death time is contained in the interval, and this death time is taken to occur at the start of the interval [12].

2.3.1. Semi-Parametric Method

Cox-Proportional Hazard Regression Model

The Cox's regression model is widely used in epidemiological research to examine the association between an exposure and a health outcome [1, 18]. The Cox proportional hazard model can be considered as consisting of two parts. The first part is the underlying hazard function, denoted λ0 (t), which is the hazard for the respective individual when all independent variable values equals zero. The second part is the effect parameters, describing how the hazard varies in response to explanatory covariates. The famous Cox model is the most popular procedure for modeling the time it takes for an event to occur and is defined as the hazard rate λi(t) for the ith subjects [19]:

where; λ0 (t) is the unspecified baseline hazard which is a nonnegative function of time. Xi is a matrix of observed covariates and β is a vector of coefficients (p x 1 column) representing the effects of the covariates. The event rates cannot be negative, Equation (1) is a semi-parametric model since the baseline hazard is nonparametric and the relative risk function is parametric. Another advantage of the Cox model is the easy interpretation of the regression parameters as log- relative risks. The β1 will for example be the effect of xi1 when we have corrected for the other covariates. β1 may be interpreted in terms of the relative risk when the covariate xi1 is increased by one unit.

If $\beta 1 > 0$ the risk of dying increases as xi1 increases, and if $\beta 1 < 0$ the risk of dying decreases as xi1 increases.

2.3.2. Parametric Survival Method

On some occasions the pattern of survivorship for our study subjects follows a predictable pattern. In this situation parametric distributions can be used to describe time to event. An advantage of using a parametric distribution is that we can reliably predict time to event well after the period during which events occurred for our observed data. Several parametric distributions are used to describe time to event data.

Accelerated Failure Time (AFT) Model

One of interests of survival analysis is to understand the relationship between time to failure and other covariates measured at the studied subjects. Parametric regression models with censored survival data using the method of maximum likelihood. In recent years' parametric model has been eclipsed by semi parametric regression model (Cox's model), which uses a method known as partial likelihood. Let Ti be a random variable denoting the failure time for the ith subject, and let xi1, xi2,…., xip be the values of p covariates for that same subject. The model is then [13]

$$\log T_i = \beta_0 + \beta_1\ x_{i1} +. + \beta p\ x_{ip} + \sigma\varepsilon_i$$

where;

1. ε_i is a random disturbance term, and
2. β…, βp, and σ are parameters to be estimated.

The only differences between the model in (3.5) and the usual linear regression models are that there is a σ before ε_i and that the dependent variable is logged. The σ can be omitted, which requires that the variance of ε_i be allowed to be different from 1. But it is simpler to fix the variance of εi at 1 and let σ change. This notational strategy could be used for linear regression models. As for the log transformation of T, its main purpose is to ensure that predicted values of T are positive. If there are no censored data, we can readily estimate this model by ordinary least squares. Simply generate a new variable, Y = log T, and use the linear regression model with Y as the dependent variable. This process yields the best linear unbiased estimates of coefficients, without distribution assumption on ε. If ε is normal, the OLS estimates will also be maximum likelihood estimates and will have minimum variance among all estimators, both linear and nonlinear [7].

The exponential model

This model specifies that ε has a standard extreme-value distribution, and constrains σ = 1.

Under exponential assumption, equation (3.5) is equivalent to

$$\text{Log } \lambda_i(t) = \beta_0^* + \beta_1^* X_{i1} + \ldots + \beta_p^* X_{ip}$$

where $\beta_j^* = -\beta_j$ for all j

The change in signs makes intuitive sense. If the hazard is high, then events occur quickly and survival times are short.

The Weibull model

The Weibull model is a slight modification of the exponential model. We retain the assumption that ε has a standard extreme-value distribution, but we relax the assumption that σ = 1. When σ > 1, the hazard decreases with time.

When 0.5 < σ < 1, the hazard is increasing at a decreasing rate. When 0 < σ < 0.5, the hazard is increasing at an increasing rate. And when σ = 0.5, the hazard function is an increasing straight line with an origin at 0.

Under Weibull assumption, equation (3.6) is equivalent to

$$\log\lambda_i(t) = \alpha \log t + \beta_0^* + \beta_1^* X_{i1} + \ldots + \beta_p^* X_{ip}$$

where; $\beta j^* = -\beta j/\sigma$ for all j and $\alpha = 1/\sigma - 1$.

Generalized Gamma Model

A generalized gamma distribution that fits neatly in the scheme we are developing, as it simply adds a scale parameter in the expression for log T, so that

$$Y = \log T = \alpha + \sigma W,$$

where; W has a generalized extreme value distribution with parameter k. The density of the generalized gamma distribution can be written as

$$f(t) = \lambda p(\lambda t)^{pk-1} e^{-(\lambda t)p} / \Gamma(k)$$

where; p = 1/σ.

The generalized gamma includes the following interesting special cases:

1. gamma, when p = 1,
2. Weibull, when k = 1,
3. Exponential, when p = 1 and k = 1.

It also includes the log-normal as a special limiting case when k → ∞

The log-normal model

T has a lognormal distribution if

Y = log T = α + σW, where; W has a standard normal distribution.

The hazard function of the log-normal distribution increases from 0 to reach a maximum and then decreases monotonically, approaching 0 as t → ∞. The generalized extreme value distribution approaches a standard normal, and thus the generalized gamma approaches a lognormal as k → ∞.

Model Selection Criterion

In the presence of many covariates that are included in the study there is a need of variable selection. In such cases, it was necessary to determine which variables should be included in fitted models. The final model was determined by means of backward elimination of these covariates. Some variables with higher p values were retained because excluding them from the model rise. The most popular and readily available methods for model fit criteria are Akaike information criteria (AIC), Bayesian information criterion (BIC) and likelihood. The AIC scored significantly, implying a poorer fit of the model. Among the most common challenges of statistical analysis, model comparison and selection are the primary issues, which have numerous procedures for choosing among a set of models. There are various methods of model selection. The Akaike information Criterion (AIC) and likelihood based criteria identifies which models within a method were relatively superior.

Model Diagnostics

The evaluations of model adequacy are often based on quantities known as residuals. It is the difference between an observed data point and a predicted or fitted value. Residuals for survival data are slightly different than for other types of models, due to censoring [20].

Schoenfeld Residuals test: is used to test the independence between residuals and time and hence is used to test the proportional Hazard assumption in Cox Model. The Schoenfeld Residuals Test is analogous to testing whether the slope of scaled residuals on time is zero or not. If the slope is not zero, then the proportional hazard assumption has been violated. In this test, there is separate residual for each individual for each covariate, and the covariate value for individuals that failed minus its expected value is defined as Schoenfeld residuals. If the plot of Schoenfeld residuals against time shows a non-random pattern, the PH assumption has been violated. The residuals can be regressed against time to further test independence between residuals and time.

3. Statistical Analysis and Discussions

3.1. Descriptive Statistics for Survival Analysis

In this study, 250 of acute coronary heart patients who followed revascularization of coronary artery treatment The percentage of covariates against status (death) of patients on the revascularization of coronary artery for treatment of coronary heart disease is computed as follows.

Table 2. *Summary statistics for discrete variable.*

		death during follow up			
		Censored		Death	
		Count	Percent	count	percent
revascularization	No	70	53.8%	60	46.1%
performed	Yes	90	75%	30	25%
ST-segment	No	80	66.6%	40	33.3%
deviation	Yes	70	53.8%	60	46.1%

The proportion of death among revascularization perfumed very less. For example, the highest percentage of death was observed for revascularization did not perform 60 (46.1%) followed by revascularization performed patient 30 (25%).

Table 3. *Descrptive of discrete variable.*

Variable	Categories	Frequency	Percent
Death during follow	Censored	169	67.6
	Death	81	32.4
revascularization	No	119	47.6
performed	yes	131	52.4
ST-segment	No	106	42.4
deviation	Yes	144	57.6

The highest percentage survive was observed in patient. From the total of 250 patients, 81 (32.4%) events were death and the rest 169 (67.6%) were censored. when we come to in cases of revascularization performed; Majority of the cases, 131 (52.4%) out of 250 patients were revascularization performed for patient and 119 (47.6%) were patients of didn't perform revascularization of coronary artery. The other thing 144 (57.6%) of coronary heart disease where ST-segment deviation and the rest 106 (42.4%) other.

Table 4. *Descriptive of continuous variables.*

Continuous Variable	N	Minimum	Maximum	mean	std. deviation mean
follow up time	250	0	180	109.85	80.227
day to revascularization	250	0	180	48.81	72.646
day to hospital stay	250	0	52	7.89	6.545
systolic blood pressure	250	0	270	140.86	30.162
age at admission	250	28	96	67.37	13.436

The mean and median time to follow up time were 109.85 and 32 days, respectively, while the minimum death of coronary heart patient were 0 days and maximum death of patient 180 days which means death of the coronary heart patient is after 6 weeks. The mean age of the patients at baseline was 67.37 years with the minimum and maximum age of 28 and 96 years, respectively. The mean of days that hospital stays is 7.89 with the minimum and maximum days of stay 0 and 52 days.

3.2. Kaplan-Meier (KM) Plot

Survival probability across categories can also be estimated. The Kaplan-Meier curves in Figure 1: illustrate survival functions according to revascularization performed, ST-segment deviation and days to revascularization. The fare of the survival curve from the y axis, is indicate that the highest the survival rates of that category.

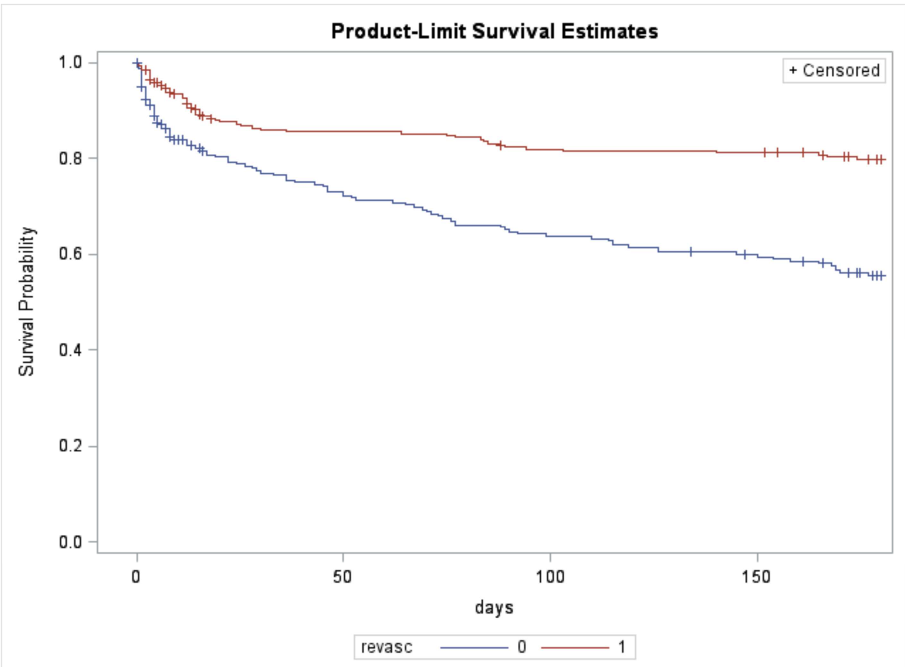


Figure 1. *Kaplan-Meier survival estimate for revasc performed patient.*

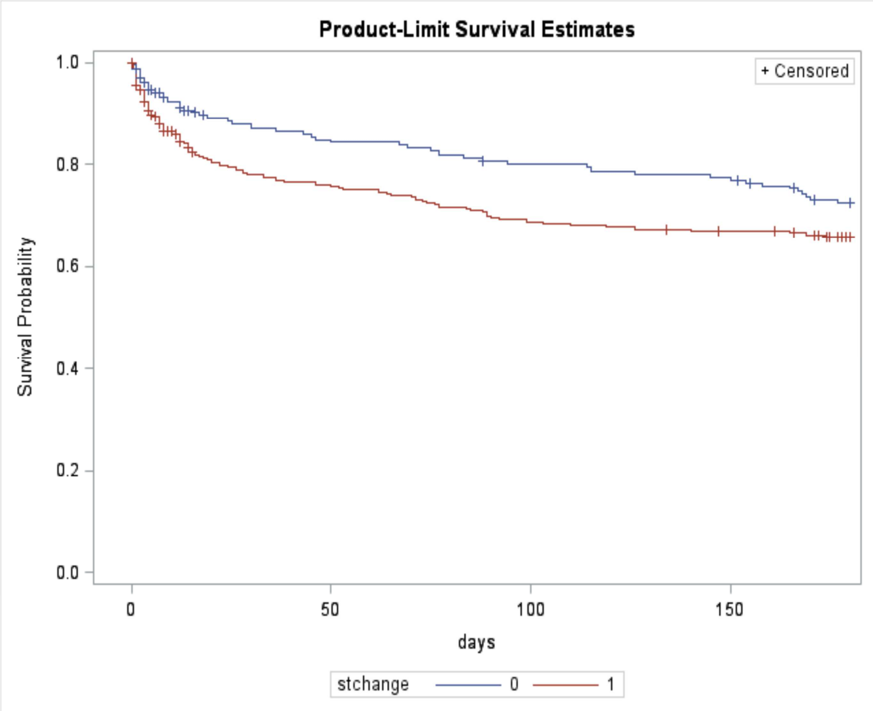


Figure 2. *Kaplan-Meier estimate for ST-segment.*

Form figure 1 we can see that the death of coronary heart patient has high in who didn't perform revascularization when compare to revascularization of coronary artery performed. From figure 2 we can conclude that death is high in patient who different from ST-segment deviation means that ST-segment deviation patient are less death.

3.3. Univariate Analysis of Cox PH Regression Model

To build a model it is recommended to perform analysis of univariate to select potential predictor variables that will be used in larger (multiple) model as a candidate variable.

Table 5. *The summary of univariate analysis is shown in the following table.*

Variables	p-value	LRT	AIC	SBC
Age	<.0001	100.1798	1829.484	1829.484
revasc	<.0001	31.7658	1829.484	1802.742
revascdays	<.0001	27.1632	1804.320	1807.344
los	0.5751	0.3236	1831.160	1834.184
sysbp	0.0004	13.0875	1818.396	1821.420
stchange	0.0508	3.9244	1827.559	1830.583

According to table 5 above the variable age, revascularization, systolic blood pressure and the days of revascularization are significant and included in the model. Because of the information form LRT, also their p- values are less than 0.05.

Cox PH Regression Model

Table 6. *Model fit statistics.*

Model Fit Statistics		
Criterion	**Without Covariates**	**With Covariates**
-2 LOG L	1641.338	1327.793
AIC	1641.338	1339.793
SBC	1641.338	1357.936

We see that the value of both AIC and BIC is decreased in model with covariates as compared to model without covariates. -2LOG L also decreased in model with covariates. The value of -2LOG L is less, which indicate that the Log likelihood is larger in model with covariates. From the Table 6: we can conclude that a model with a covariate is best explains the change in survival or hazard rate of the patients.

Table 7. *Testing global hypothesis.*

Testing Global Null Hypothesis: BETA=0			
Test	**Chi-Square**	**DF**	**Pr > ChiSq**
Likelihood Ratio	313.5452	6	<.0001
Score	446.0732	6	<.0001
Wald	238.2835	6	<.0001

Table 7: indicated that all three tests are significantly different from zero and yield similar conclusions, that is, the model with explanatory variables was more effective than the null model. The Likelihood ratio test indicates that the explanatory variables having a contribution to the likelihood function, and this is supported by model fit statistics. At least one of the variables is globally important in explaining in changes the survival time or hazard rate of the patients.

Table 8. *Type 3 Tests.*

Effect	DF	Wald Chi-Square	Pr > ChiSq
Revasc	1	118.5399	<.0001
Revascdays	1	123.5468	<.0001
Los	1	1.9207	0.1658
Age	1	30.2155	<.0001
Sysbp	1	3.0381	0.0813
Stchange	1	0.4112	0.5213

The above Table 8: that the survival and hazard rate of death coronary heart patients in case of revascularization performed was statistically different with these patient who had performed revascularization of coronary artery and who hadn't. also fore age, los are similar interpretation but the survival time and hazard rate of the death of patient during follow up in the categories of other variables weren't significantly differing from category to category.

Table 9. *Multivariate analysis of Cox PH Regression Model.*

Parameter	DF	Parameter Estimate	Standard Error	Chi-Square	Pr > ChiSq	Hazard Ratio	95% Confidence	Label
Revasc	1	-3.38584	0.310	118.539	<.0001	0.034	0.018	0.062
Revascdays	1	-0.02718	0.002	123.546	<.0001	0.973	0.969	0.978
Los	1	-0.01868	0.51348	1.9207	0.0358	0.981	0.956	1.008
Age	1	0.03265	0.00594	30.2155	<.0001	1.033	1.021	1.045
Sysbp	1	-0.00530	0.00304	3.0381	0.0813	0.995	0.989	1.001

The fitted Cox PH regression model can be written as: -

$$\lambda i(t/Z) = \lambda o(t) \exp(-3.39 revasc\ i + 0.0304 agei - 0.02718 revascdaysi)$$

Patients who revascularization performed are surviving from the disease by 3.40% when compared as who did not perform the revascularization. Patients at age are significantly; indicate that they have similar hazard or the same chance to death by the coronary heart disease. From the Table 8: we have seen that categorical variables such as st change (ST-segment deviation), revascularization perform and revascularization days type order by physician to patients with their categories and continuous variables such as age, systolic blood pressure and los (days of hospital stays) were not significance and not important in explaining the change in survival time and hazard rate. But when we interact either with other significant variables or time they may be important in explaining the change in survival and hazard rate likewise, its point estimate will be changed.

3.4. Accelerated Failure Time (AFT) Model

All AFT models are named for the distribution of T rather than the distribution of ε or log T. The reason for allowing different distribution assumptions is that they have different implications for the shapes of hazard function.

Table 10. *Linear Hypotheses Testing Results.*

Linear Hypotheses Testing Results				
Label	**Wald**	**Chi-Square**	**DF**	**Pr >ChiSq**
Tes	proportionality	8.0139	7	0.833

Table 11. *AFT MODEL.*

Distribution	AIC	BIC	-2Loglikelihood
Gamma	1916.561	3931.808	1906.561
Exponential	2016.236	2027.831	1067.440
Weibull	1912.749	2086.37	2015.204

From the above table the Weibull distribution has less AIC and high Log likelihood values than other distributions this leads to conclude Weibull distribution is better for this dataset. But according to the BIC value gamma distribution has least value than the other distributions. This seems makes contradict to the value of AIC and Log likelihood and this need inferential (hypothesis) test.

We have seen that the AFT model encompasses a number of sub models that differ in the assumed distribution for T. Clearly, we need some way of deciding between the models, i. e., the shapes of hazard. Here we introduced the likelihood ratio test for comparing nested models. Gamma model is said to be nested within Weibull model. Let's select the appropriate model using the likelihood ratio test for the coronary heart patient data.

H0: gamma model H1: Weibull model

The log-likelihood for Weibull model is 2015.20 and the log-likelihood for Gamma model is 1906.56. The likelihoodratio Chi-square statistic is -2 (1906.56-2015.20) =1015.44 with 1 degree of freedom. Clearly, we reject the null hypotheses, that is to say Weibull model fits the coronary heart patient data better than gamma model and it support the decision on the value of AIC and Log likelihood in Table 11.

3.5. Model Diagnostics

Residual plots

Schoenfeld residual plot

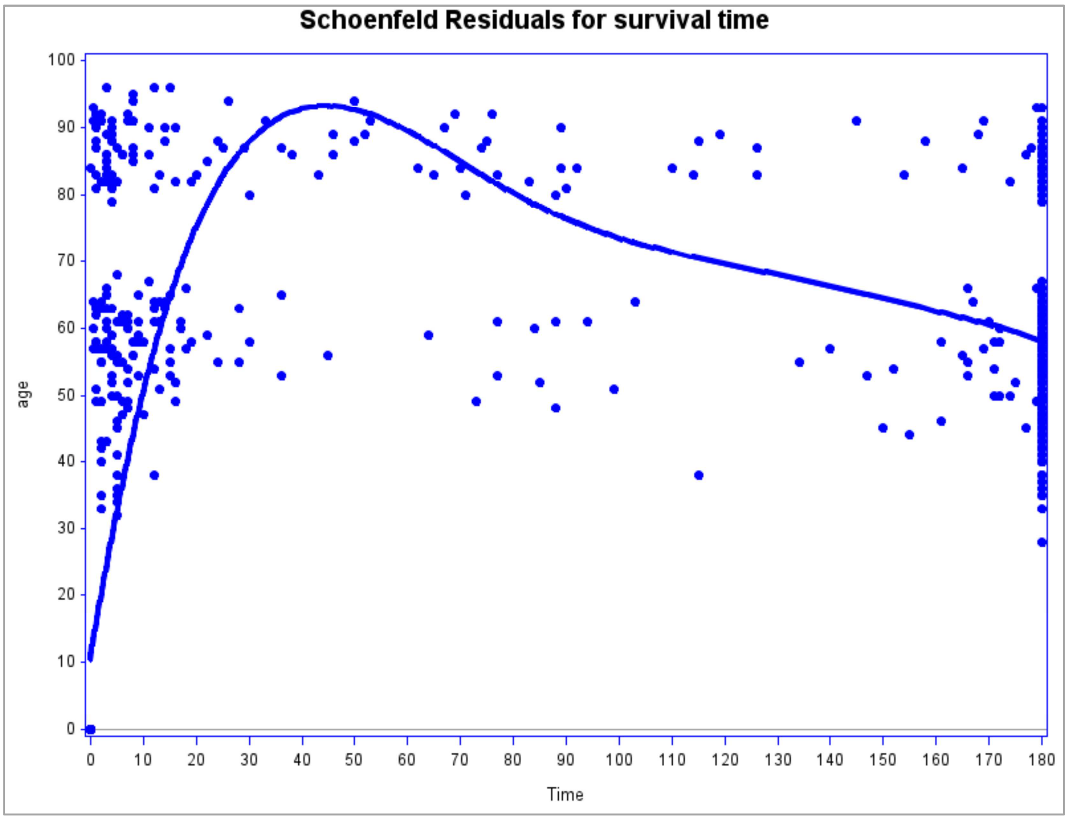


Figure 3. *Schoenfeld for age.*

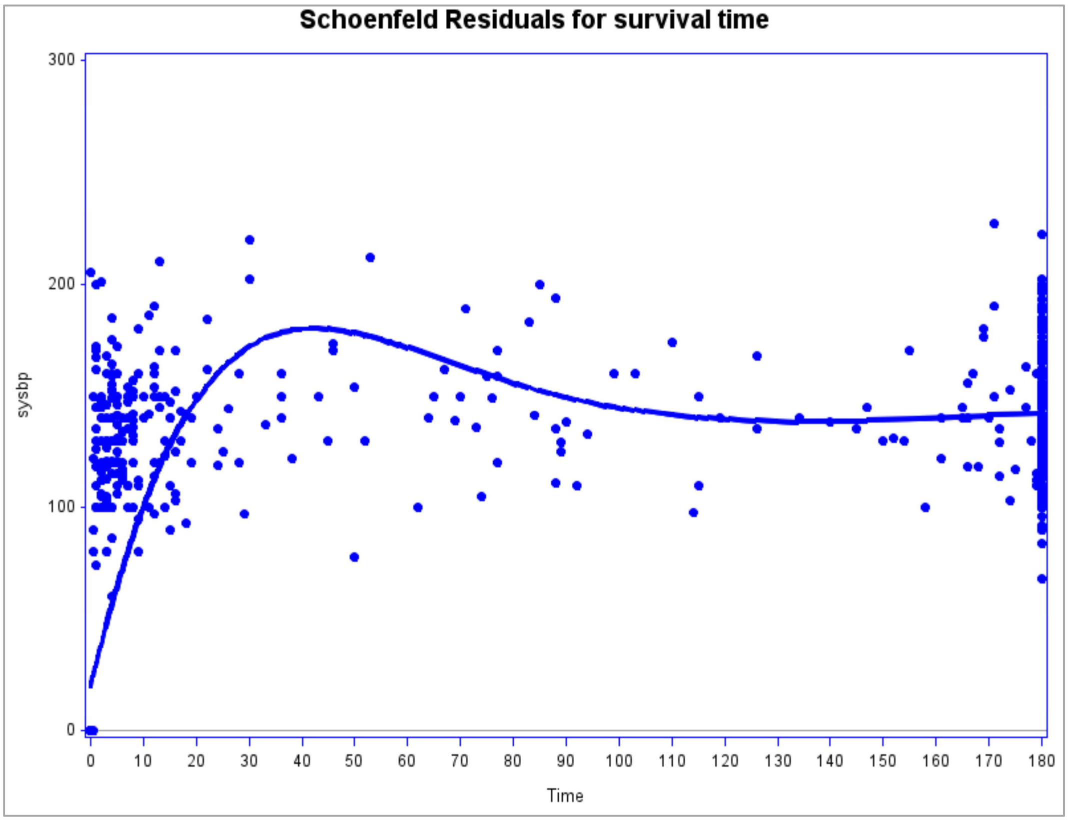
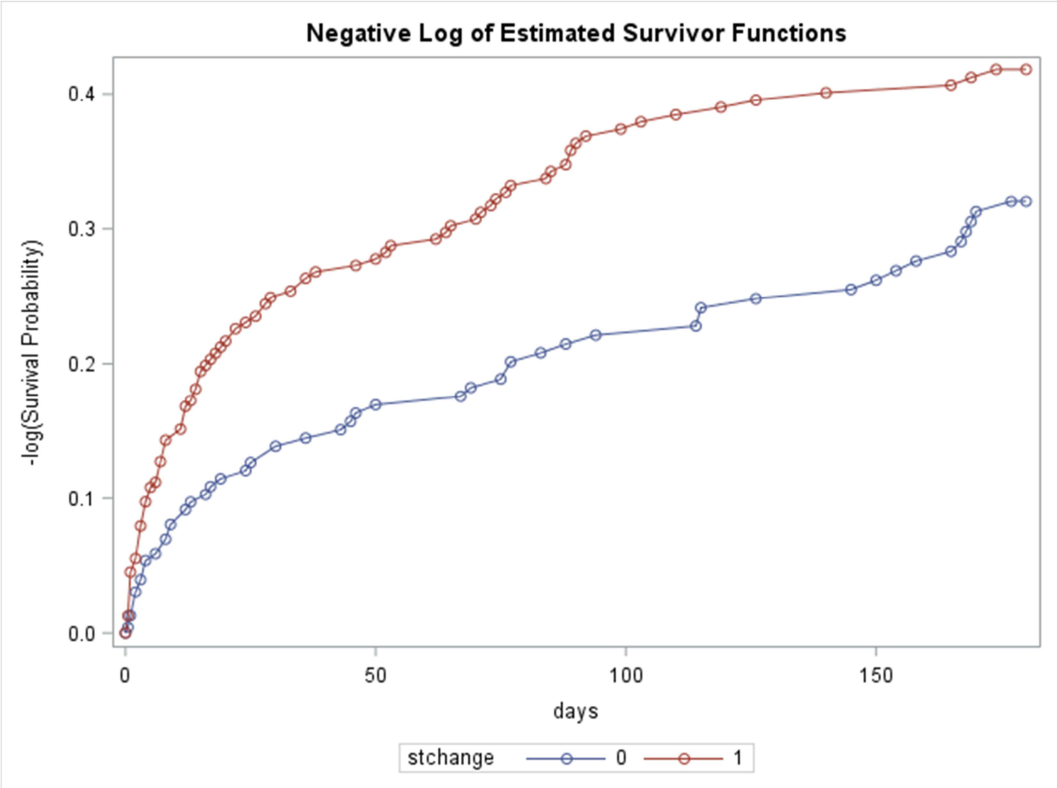


Figure 4. *Schoenfeld for st-segment.*

When we see the above residual plots: The plots show the Schoenfeld residuals versus time for survival data, Since the curves was close to zero line, we concluded that the PH assumption was not violated for the covariates age and systolic blood pressure but, for revascularization the plot shows slight deviation from the assumption of proportionality.



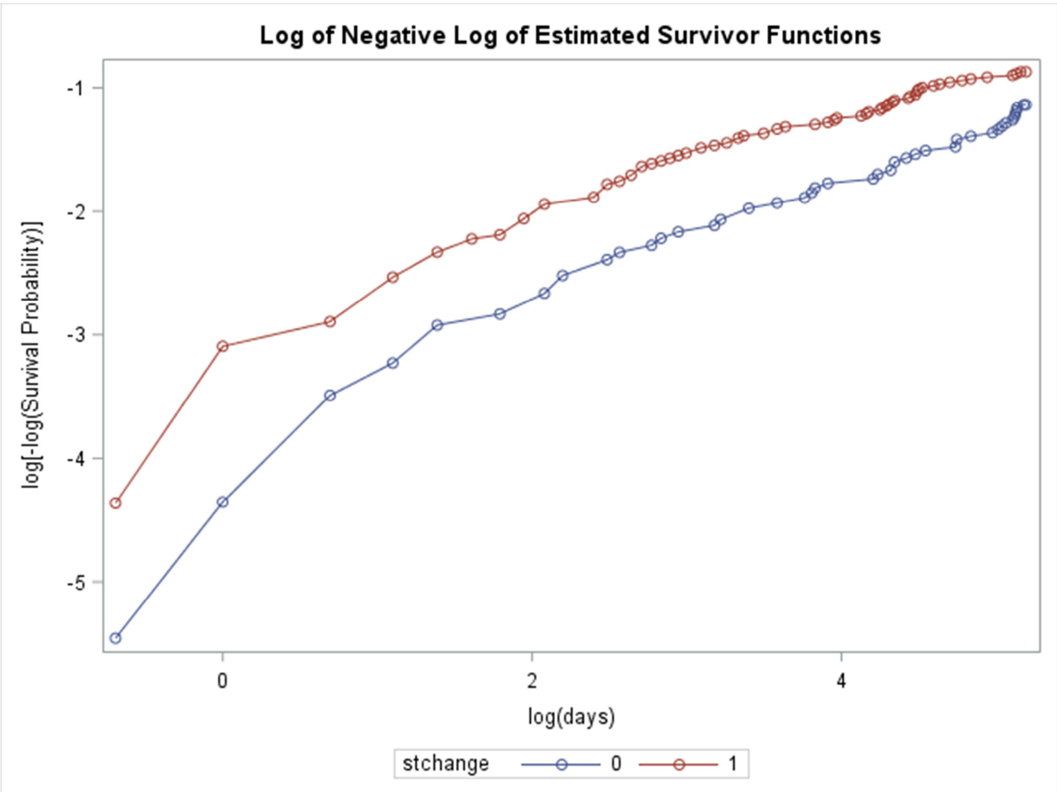


Figure 5. *Plotting log [- log(̂(ti)] Vs log(t) should yield a straight line passes through the origin.*

The overall graphical approaches to assess the cox PH assumptions indicates that, for some of the plot assumption is fulfilled but we have a doubt for others so we continue to inferential test.

4. Conclusion and Recommendation

4.1. Conclusion

Conclusions According to the results of this study the death during follow up of the revascularization of coronary artery is affected by factors such as age of patients, revascularization performed, and revascularization days. The hazard ratio for two groups is proportional throughout the days as shown by this paper. In these study coronary heart patients of do not preform revascularization of coronary artery died more quickly than patient who performs the revascularization artery. According to this project among the covariates identified to affect the follow up days, the variables age and revascularization are found to influence the days (time) strongly. The variable st segment deviation also affects the follow up days of patient to some extent. Generally Weibull model is best model to fit this data from parametric model.

4.2. Recommendations

Since the death of coronary heart patients depends on age of the individual, patients have high age must go to the hospital in order to get the treatment of revascularization of coronary artery for cure from the disease that treatment under consideration.

For Patient of coronary heart disease, the most survive method from death was revascularization of coronary artery preformed so patient with coronary heart disease the use of revascularization of coronary artery recommended.

The st-segment deviation has the appropriate when compared form other electrocardiogram like st-segment elevation for coronary heart disease patient.

Special treatment should be afforded for patients of age 49 and above to decrease the time of survive from the coronary heart disease.

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