Task_3-report

November 29, 2025

[1]:
```
#https://www.emilyzabor.com/survival-analysis-in-r.html
data <- read.csv("Data_T3.csv")
```

[2]:
```
# a first look at the data
head(data)
summary(data)
```

A data.frame: 6 × 9

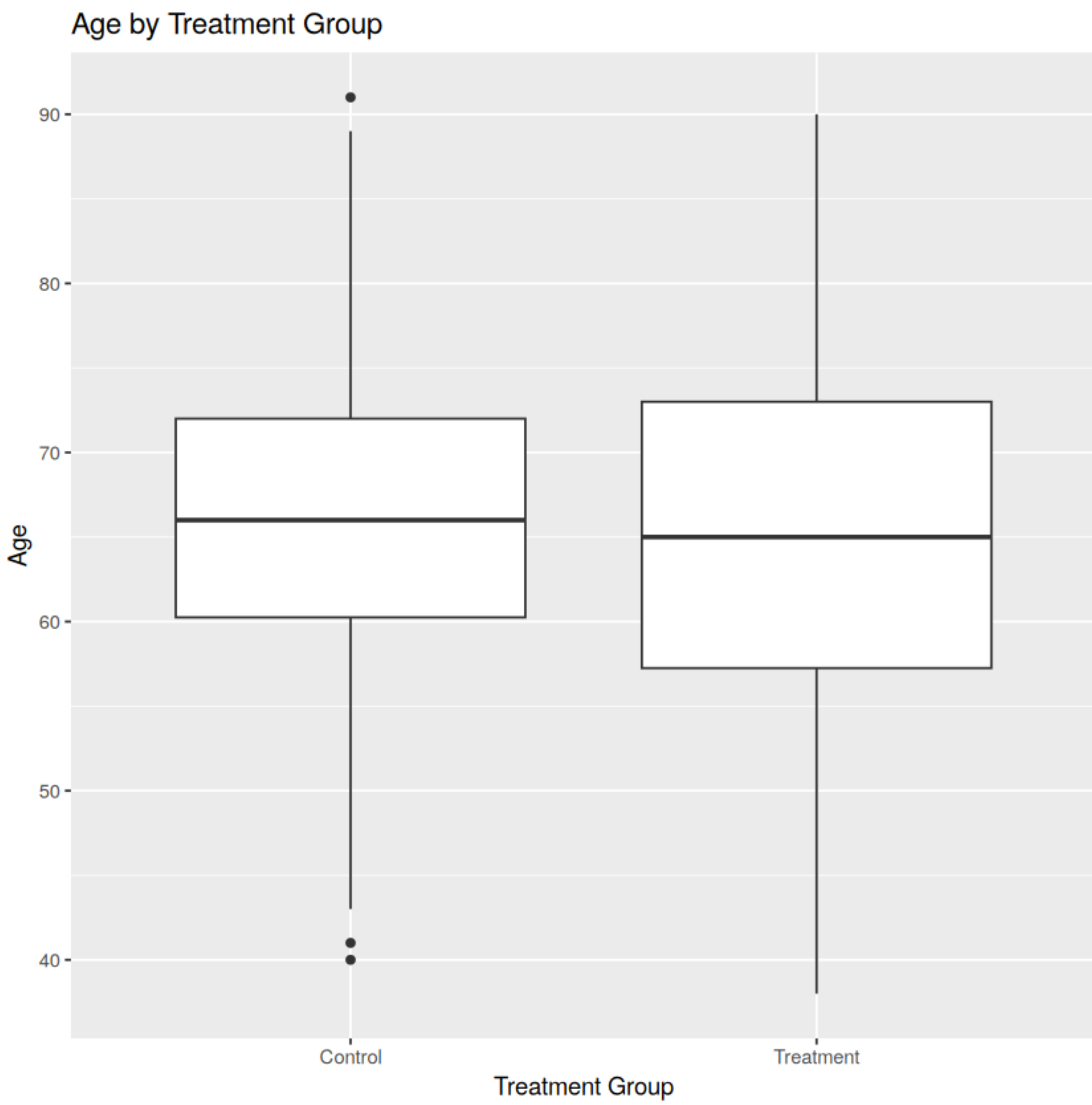
	X <int>	ID <int>	TreatmentGroup <chr>	Age <int>	Sex <chr>	ECOG_PS <int>	GFR <int>	Time <dbl>	E <
1	1	1	Treatment	73	Female	2	83	0.6	1
2	2	2	Treatment	62	Male	0	86	6.3	1
3	3	3	Treatment	61	Female	0	98	57.7	0
4	4	4	Treatment	66	Male	1	58	0.7	1
5	5	5	Treatment	88	Female	0	120	30.7	0
6	6	6	Treatment	73	Male	0	55	6.5	1

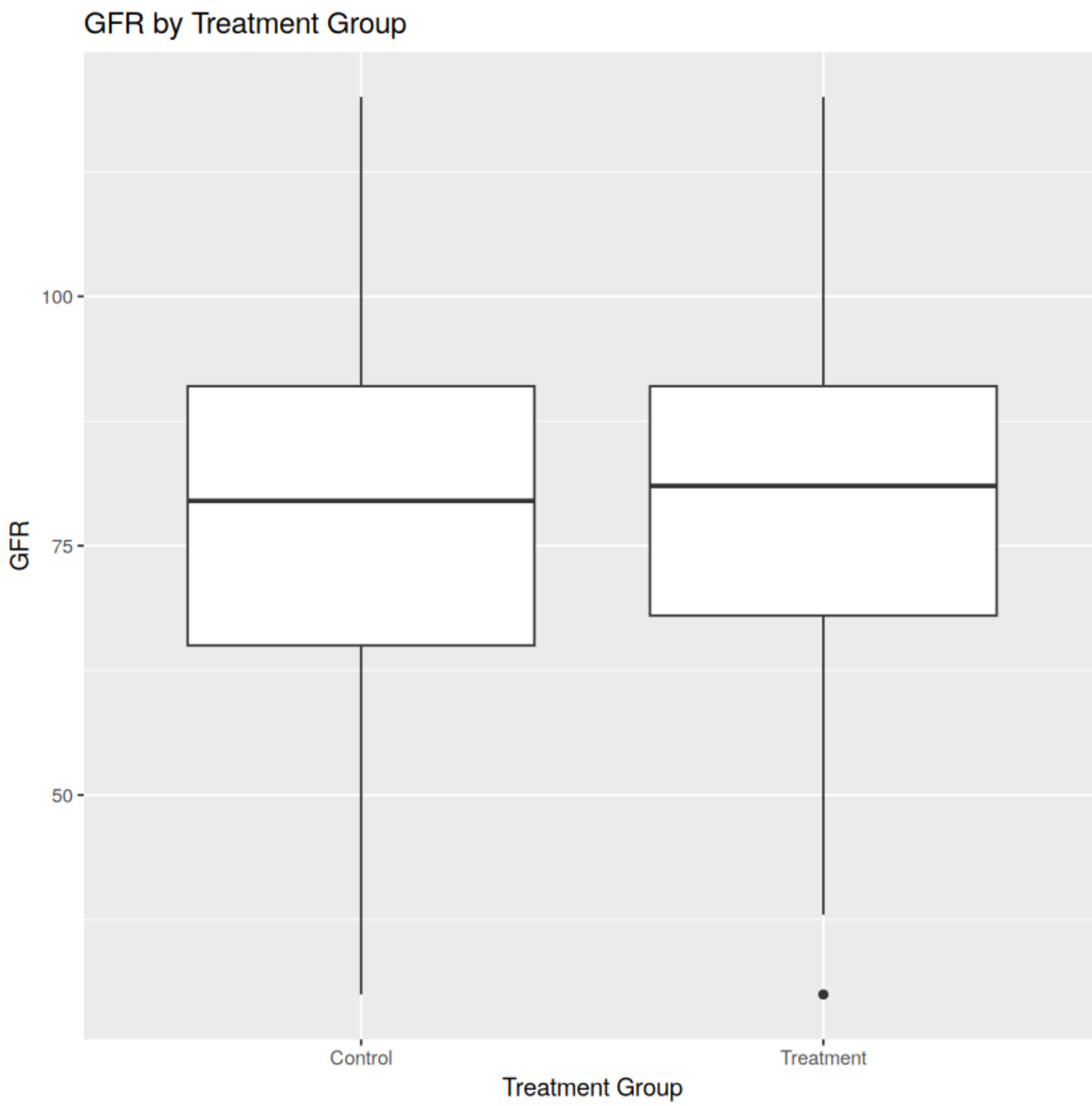
```
       X                ID         TreatmentGroup          Age
 Min.   :  1.00   Min.   :  1.00   Length:300         Min.   :38.0
 1st Qu.: 75.75   1st Qu.: 75.75   Class :character   1st Qu.:59.0
 Median :150.50   Median :150.50   Mode  :character   Median :65.0
 Mean   :150.50   Mean   :150.50                      Mean   :65.3
 3rd Qu.:225.25   3rd Qu.:225.25                      3rd Qu.:72.0
 Max.   :300.00   Max.   :300.00                      Max.   :91.0
     Sex               ECOG_PS            GFR              Time
 Length:300         Min.   :0.0000   Min.   : 30.00   Min.   : 0.000
 Class :character   1st Qu.:0.0000   1st Qu.: 66.00   1st Qu.: 2.600
 Mode  :character   Median :1.0000   Median : 81.00   Median : 5.900
                    Mean   :0.8167   Mean   : 78.89   Mean   : 9.673
                    3rd Qu.:1.0000   3rd Qu.: 91.00   3rd Qu.:13.600
                    Max.   :2.0000   Max.   :120.00   Max.   :57.700
     Event
 Min.   :0.00
 1st Qu.:1.00
 Median :1.00
 Mean   :0.76
 3rd Qu.:1.00
 Max.   :1.00
```

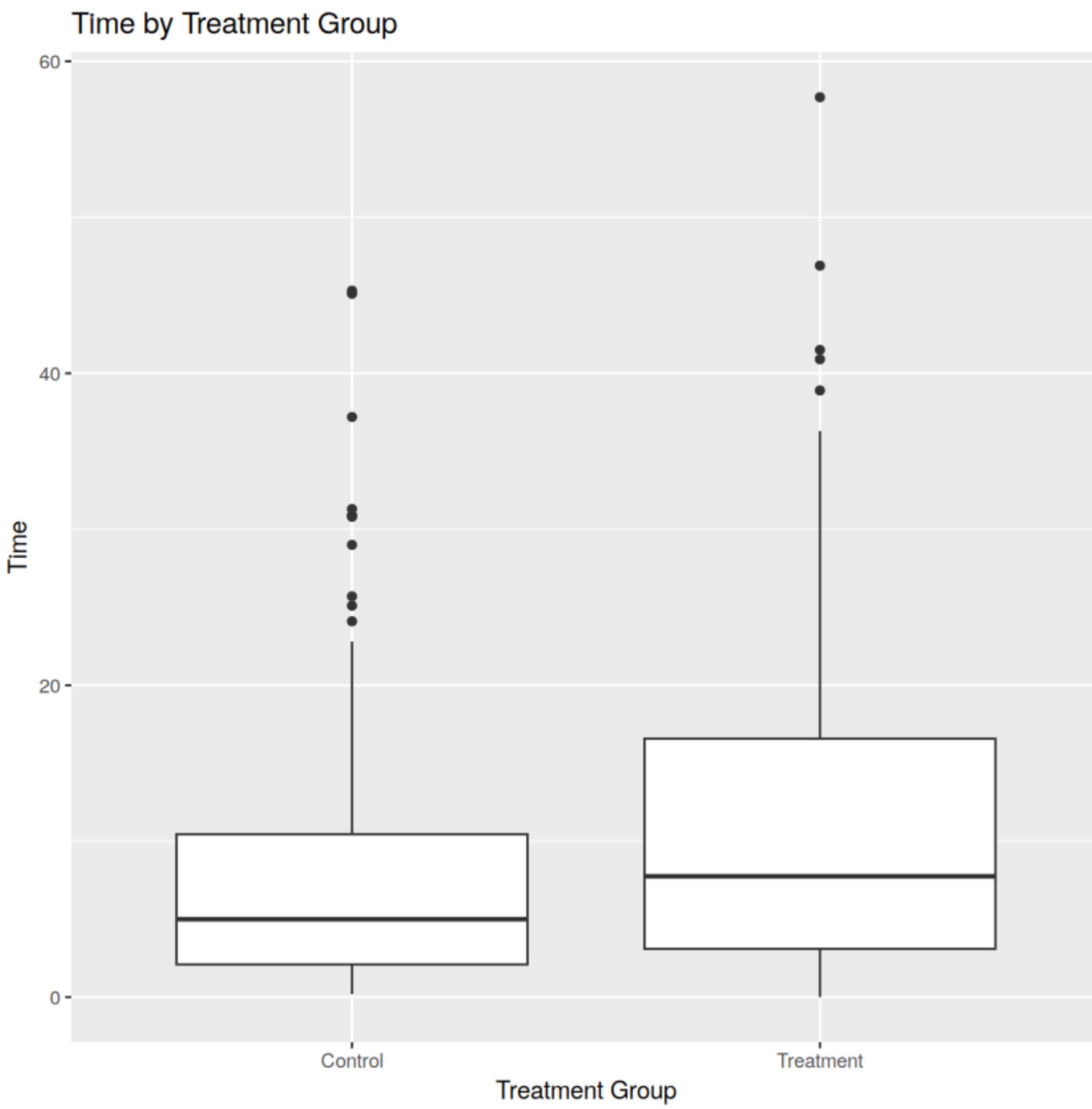
[3]:
```
dim(data)
```

1. 300 2. 9

[5]:
```
# Box plots to compare distributions between treatment groups
ggplot(data, aes(x = TreatmentGroup, y = Age)) +
  geom_boxplot() +
  labs(title = "Age by Treatment Group", x = "Treatment Group", y = "Age")

ggplot(data, aes(x = TreatmentGroup, y = GFR)) +
  geom_boxplot() +
  labs(title = "GFR by Treatment Group", x = "Treatment Group", y = "GFR")

ggplot(data, aes(x = TreatmentGroup, y = Time)) +
  geom_boxplot() +
  labs(title = "Time by Treatment Group", x = "Treatment Group", y = "Time")
```




GFR by Treatment Group
100
75
50
GFR
Control
Treatment
Treatment Group

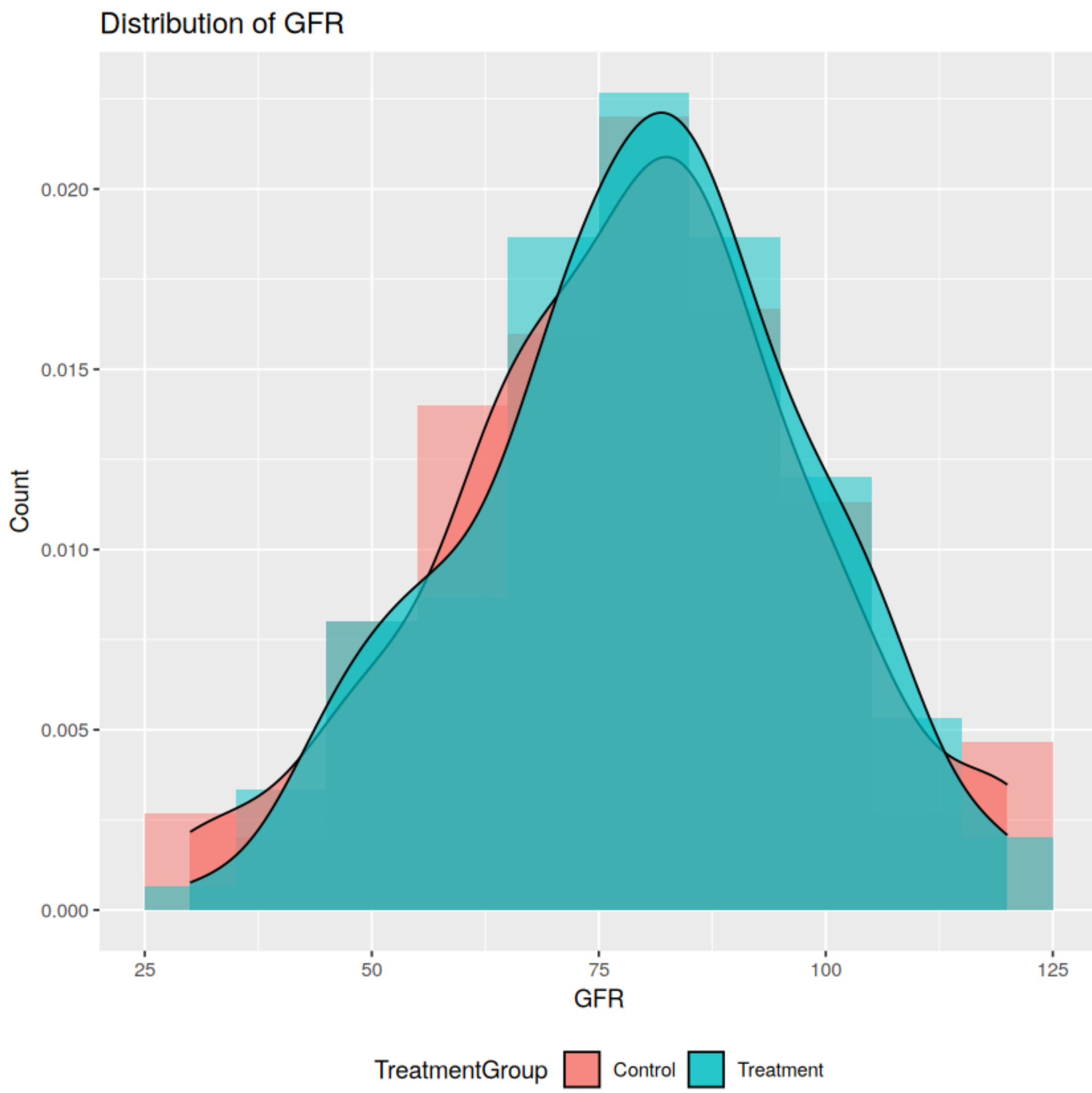


[6]:
```
# Histograms for continuous variables
ggplot(data, aes(x = Age, fill = TreatmentGroup)) +
 geom_histogram(aes(y = ..density..), alpha = 0.5, position = "identity", bins␣
 ↪= 10) +
  geom_density(alpha = 0.7) +
  labs(title = "Distribution of Age", x = "Age", y = "Count") +
  theme(legend.position = "bottom")

ggplot(data, aes(x = GFR, fill = TreatmentGroup)) +
geom_histogram(aes(y = ..density..), alpha = 0.5, position = "identity", bins =␣
 ↪10) +
  geom_density(alpha = 0.7) +
```

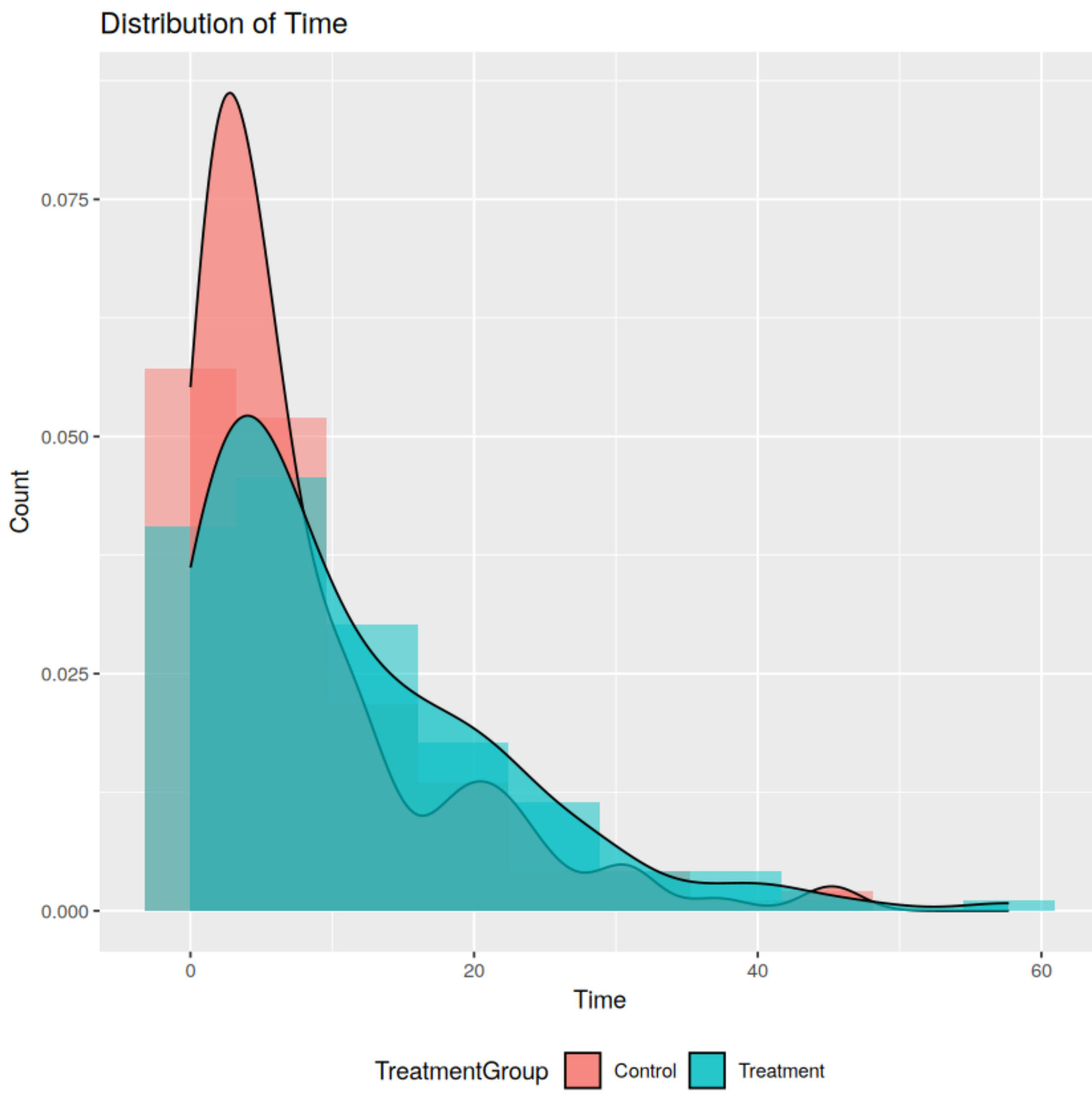
```r
  labs(title = "Distribution of GFR", x = "GFR", y = "Count") +
  theme(legend.position = "bottom")

ggplot(data, aes(x = Time, fill = TreatmentGroup)) +
  geom_histogram(aes(y = ..density..), alpha = 0.5, position = "identity", bins
 ↪= 10) +
  geom_density(alpha = 0.7) +
  labs(title = "Distribution of Time", x = "Time", y = "Count") +
  theme(legend.position = "bottom")

# Bar plots for categorical variables
ggplot(data, aes(x = Sex, fill = TreatmentGroup)) +
  geom_bar(position = "dodge") +
  labs(title = "Distribution of Sex", x = "Sex", y = "Count")
```

```
Warning message:
"The dot-dot notation (`..density..`) was deprecated in ggplot2 3.4.0.
 Please use `after_stat(density)` instead."
```

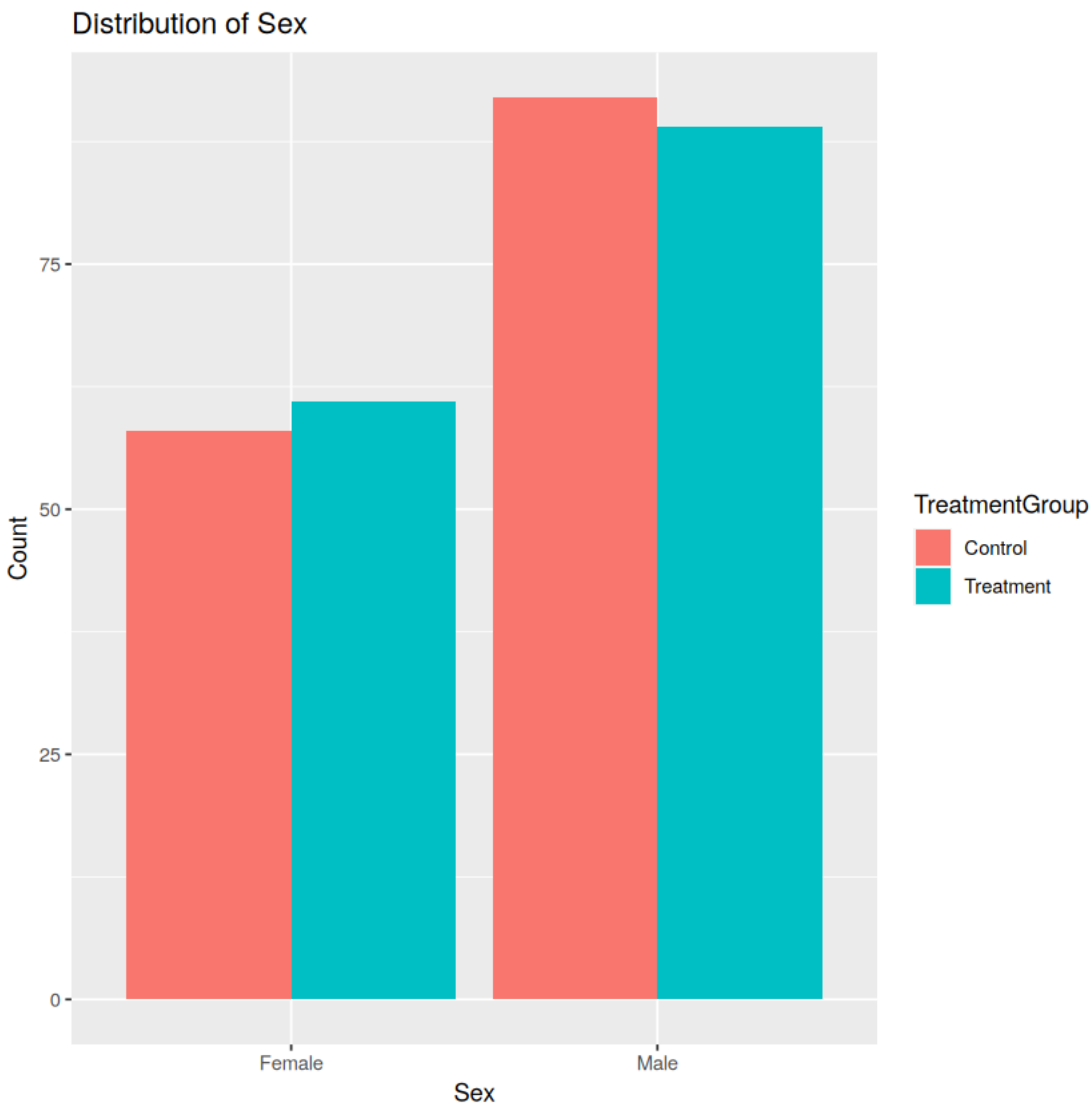

Distribution of Age
Count
0.04
0.03
0.02
0.01
0.00
30
40
50
60
70
80
90
Age
TreatmentGroup
Control
Treatment



Distribution of GFR
Count
0.020
0.015
0.010
0.005
0.000
25
50
75
100
125
GFR
TreatmentGroup
Control
Treatment

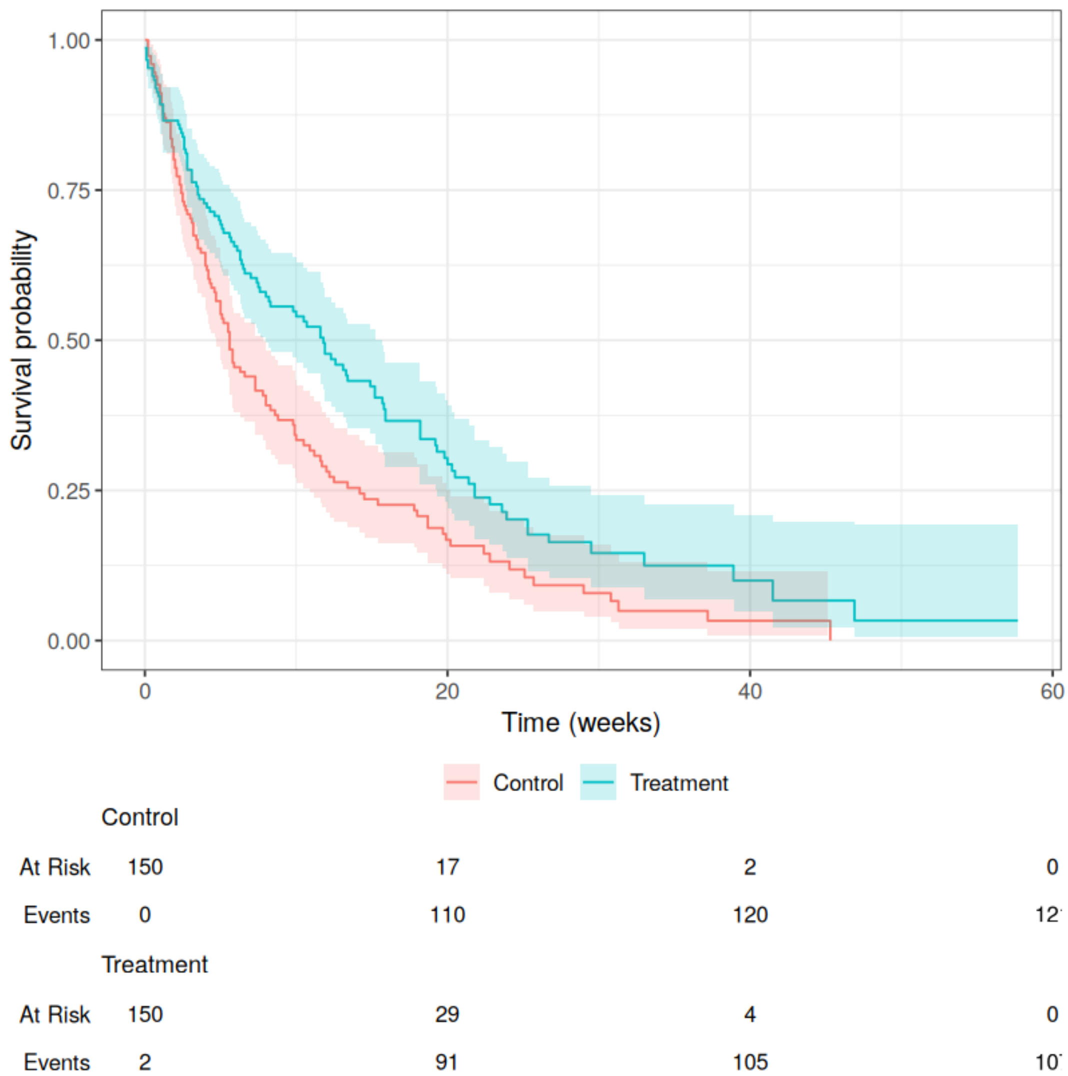


Distribution of Time
0.075
0.050
0.025
0.000
Count
0
20
40
60
Time
TreatmentGroup
Control
Treatment



From the visual graphs we can observe quite a even split between the control and treatment group, further more the number of male are more in number making the data is skewed. For GFR, Age the data distribution look quite normal but time distribution is heavily left skewed.

[7]:
```
# Kaplan-Meier survival curves with confidence intervals by treatment group
survfit2(Surv(Time, Event) ~ TreatmentGroup, data = data) |>
  ggsurvfit() +
  labs(
    x = "Time (weeks)",
    y = "Survival probability"
  )+
  add_confidence_interval() +
  add_risktable()
```



[8]:
```r
summary(survfit2(Surv(Time, Event) ~ TreatmentGroup, data = data), times = 5)
```

```
Call: survfit(formula = Surv(Time, Event) ~ TreatmentGroup, data = data)

                TreatmentGroup=Control
        time        n.risk       n.event      survival       std.err lower 95% CI
       5.000        77.000        65.000         0.543         0.042        0.467
upper 95% CI
       0.632

                TreatmentGroup=Treatment
        time        n.risk       n.event      survival       std.err lower 95% CI
      5.0000       99.0000       45.0000        0.6927        0.0382       0.6217
```

```
upper 95% CI
      0.7718
```

We are using Kaplan-Meier survival modeling here, a thing to observer here the early treatment for first 4 weeks we can see the control group having better survival odds but with increasing time the treatment shows effect and we can see uplift of the treatment course.

Can be observed in the graphs.

[9]:
```
# Fit the Cox PH model
cox_model <- coxph(Surv(Time, Event) ~ TreatmentGroup + Age + Sex + ECOG_PS +
 ↪GFR, data = data)

# Summarize the model
summary(cox_model)
```

```
Call:
coxph(formula = Surv(Time, Event) ~ TreatmentGroup + Age + Sex +
    ECOG_PS + GFR, data = data)

  n= 300, number of events= 228

                            coef exp(coef)  se(coef)      z Pr(>|z|)
TreatmentGroupTreatment -0.525216  0.591428  0.138716 -3.786 0.000153 ***
Age                     -0.010326  0.989727  0.006697 -1.542 0.123080
SexMale                 -0.086113  0.917490  0.137160 -0.628 0.530115
ECOG_PS                  0.444375  1.559514  0.091175  4.874 1.09e-06 ***
GFR                     -0.013653  0.986439  0.003674 -3.716 0.000202 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

                        exp(coef) exp(-coef) lower .95 upper .95
TreatmentGroupTreatment    0.5914     1.6908    0.4506    0.7762
Age                        0.9897     1.0104    0.9768    1.0028
SexMale                    0.9175     1.0899    0.7012    1.2005
ECOG_PS                    1.5595     0.6412    1.3043    1.8647
GFR                        0.9864     1.0137    0.9794    0.9936

Concordance= 0.646  (se = 0.019 )
Likelihood ratio test= 54.07  on 5 df,   p=2e-10
Wald test            = 54.51  on 5 df,   p=2e-10
Score (logrank) test = 55.88  on 5 df,   p=9e-11
```

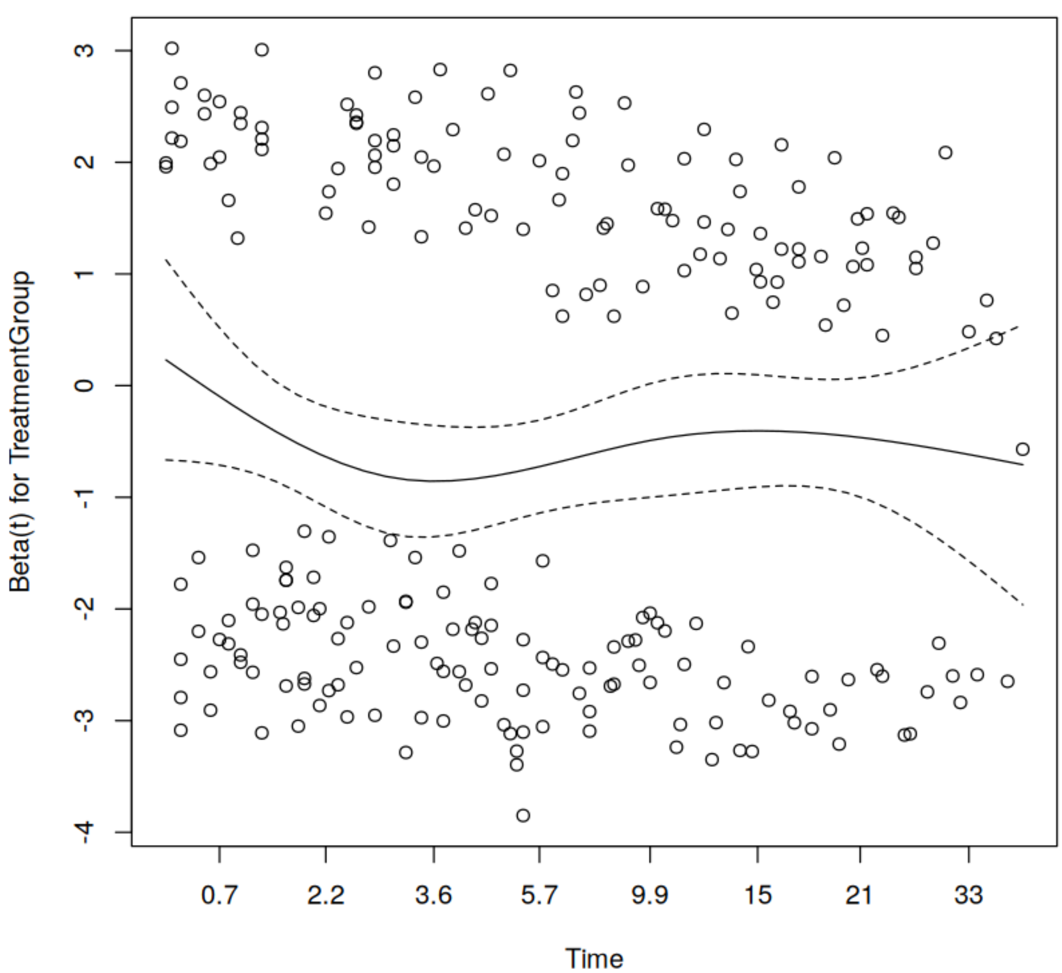
Key observations: After analy the Pr(>|z|), we find 3 factors to be significant - TreatmentGroup, ECOG_PS & GFR * TreatmentGroup = Treatment, P value is quite small and we can see there is a negative coefficient meaning there is an inverse correlation to the risk of death, meaning the person having the treatment has a higher chance of recovery and by exp(coef) reduces it by 41% *

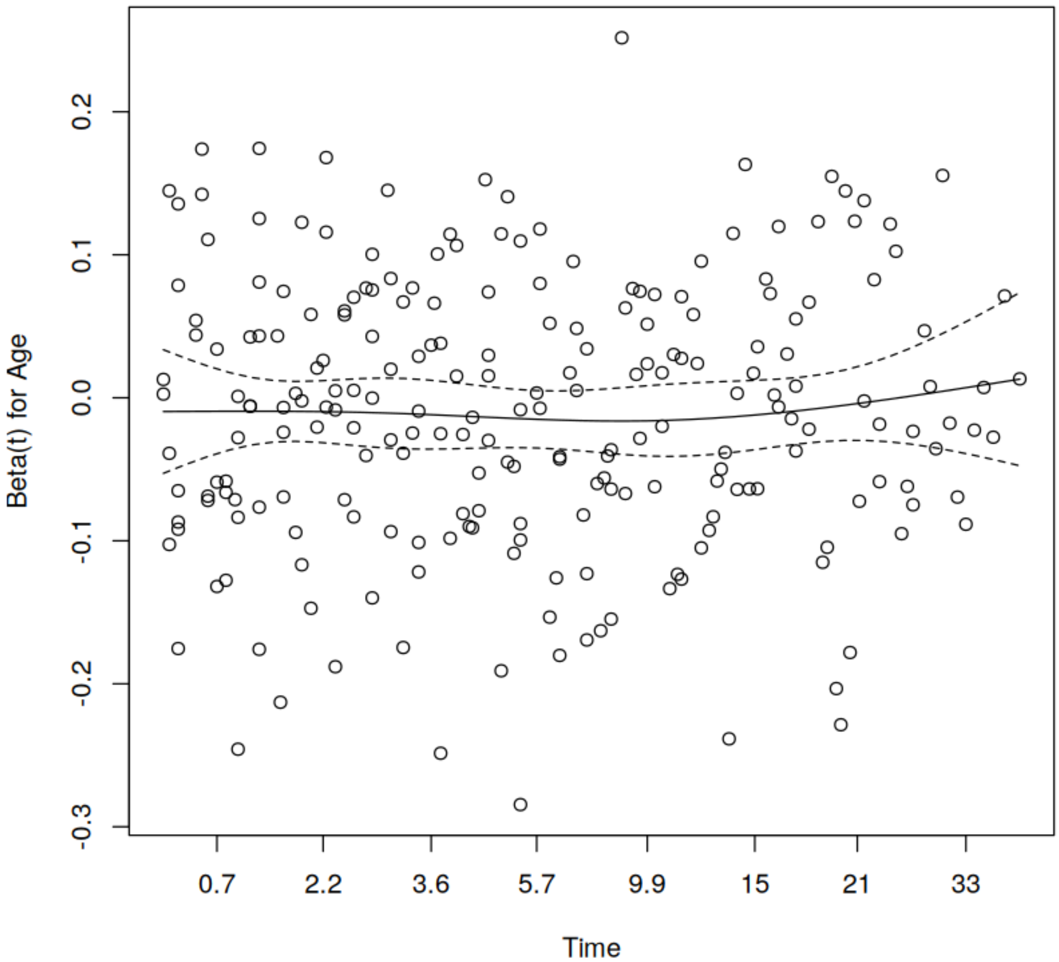
ECOG_PS, p value is quite small and is significant furthermore it has a positive correlation and by looking the exp(coef) we can can it increases the chance of death. * GFR, is relevant due to the small p value, and has as negative relation i.e. 1 unit increase in GFR adds decreased risk by 1.4%.

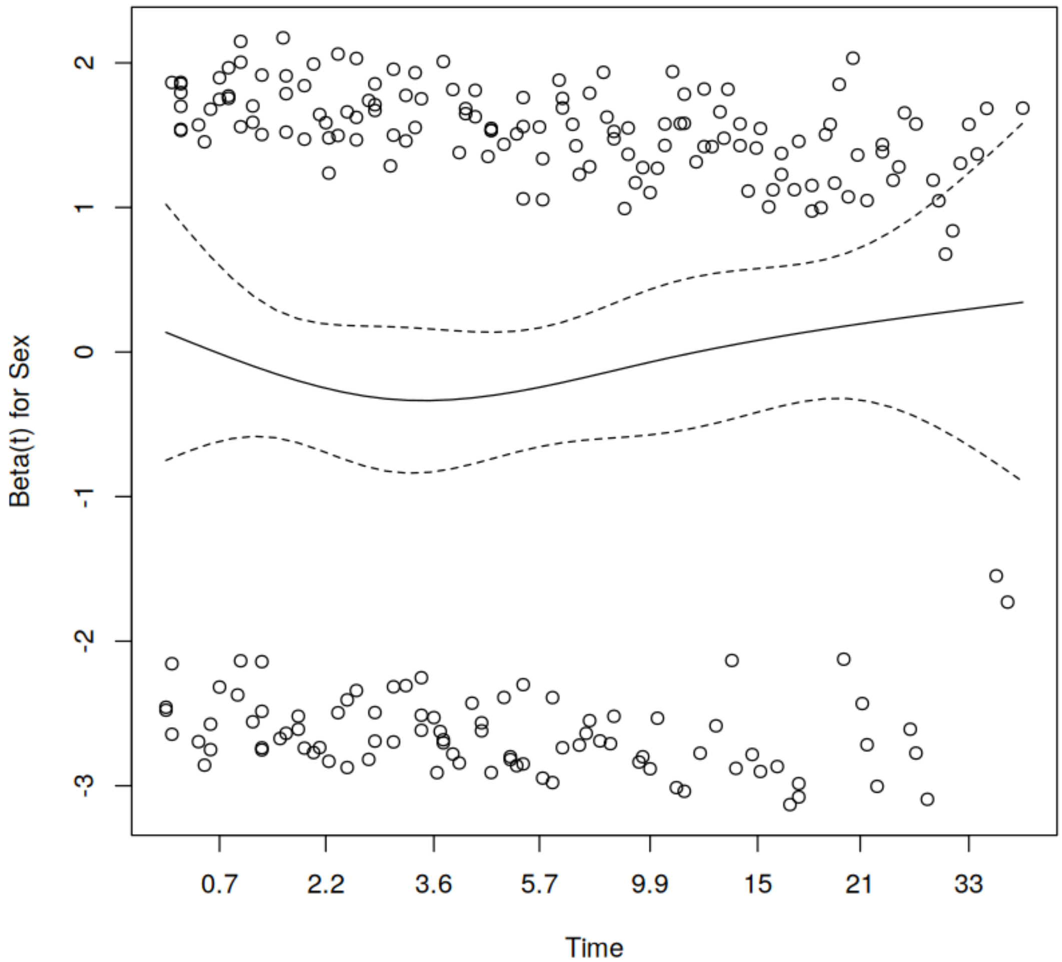
[12]:
```
temp <- cox.zph(cox_model)
```

[ ]:
```
print(temp)                    # display the results
plot(temp)                     # plot curves
```

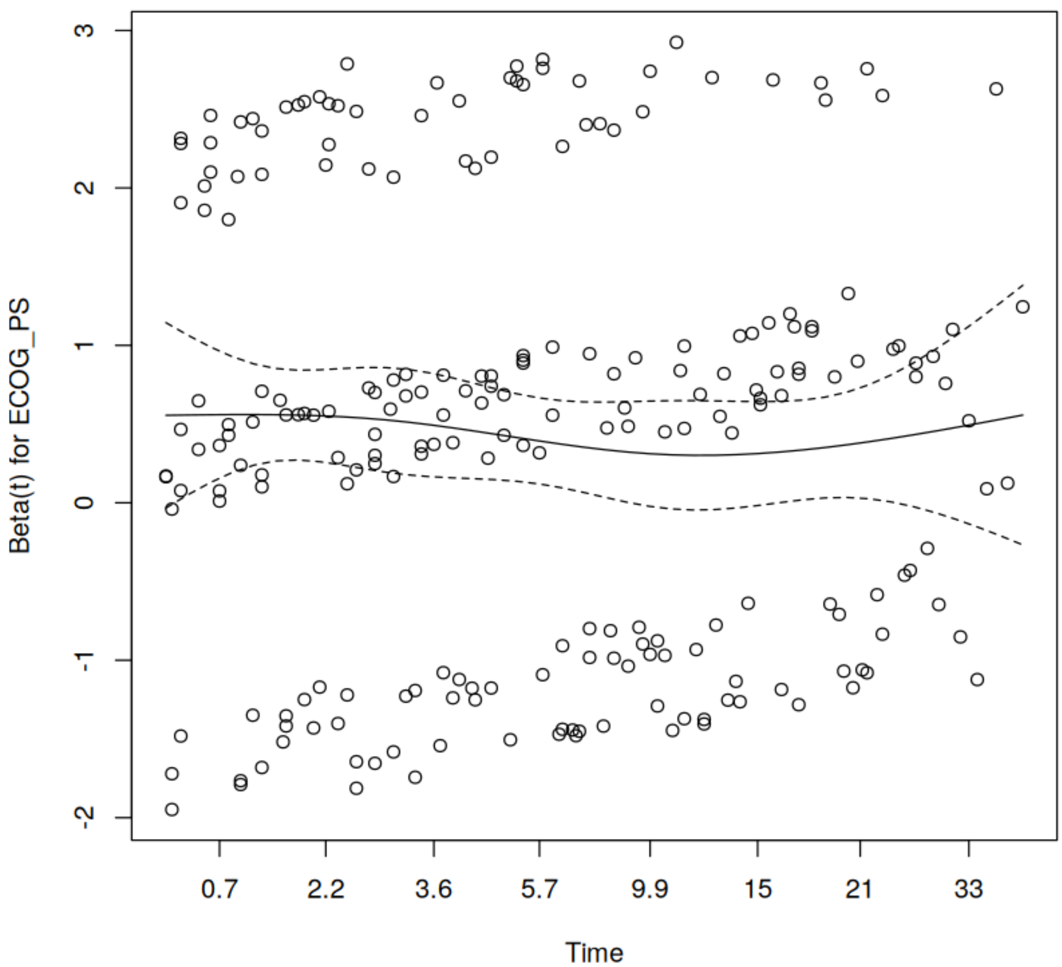
```
               chisq df    p
TreatmentGroup 0.528  1 0.47
Age            0.172  1 0.68
Sex            0.755  1 0.38
ECOG_PS        0.686  1 0.41
GFR            0.556  1 0.46
GLOBAL         2.249  5 0.81
```

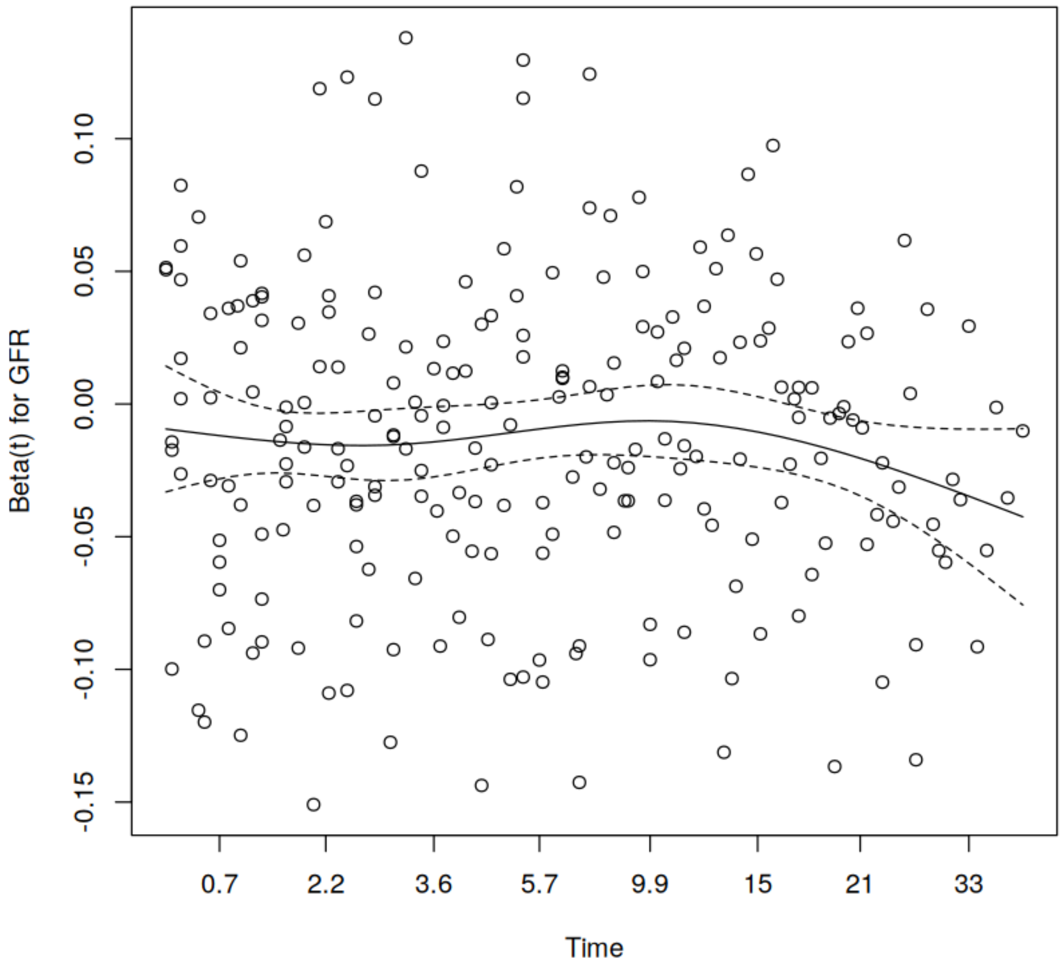



Beta(t) for Age
0.2
0.1
0.0
-0.1
-0.2
-0.3
0.7
2.2
3.6
5.7
9.9
15
21
33
Time



Beta(t) for Sex
2
1
0
-1
-2
-3
0.7
2.2
3.6
5.7
9.9
15
21
33
Time


Beta(t) for ECOG_PS
3
2
1
0
-1
-2
0.7
2.2
3.6
5.7
9.9
15
21
33
Time



Proportionality hazard assumption holds for all the cases as the p value is significantly greater than 0.05 for all cases.

[10]:
```
# Extract the hazard ratios and 95% CI
hazard_ratios <- coef(cox_model)
conf_int <- confint(cox_model)

# Print the results
print(paste("Hazard Ratios and 95% CI:"))
print(hazard_ratios)
print(conf_int)
```

```
[1] "Hazard Ratios and 95% CI:"
```

```
TreatmentGroupTreatment                    Age                SexMale
            -0.52521603            -0.01032611            -0.08611317
                ECOG_PS                    GFR
             0.44437455            -0.01365335
                              2.5 %       97.5 %
TreatmentGroupTreatment -0.79709423 -0.253337834
Age                     -0.02345135  0.002799134
SexMale                 -0.35494193  0.182715596
ECOG_PS                  0.26567435  0.623074745
GFR                     -0.02085457 -0.006452126
```

Looking at the HR ratios of the Cox PH model, we draw similar conclusions as before. Furthermore there are some slightly significant observations that can be drawn are being Male reduced the risk marginally or with age the risk goes down as well. But looking at the data imbalance we can see the data to be favoring men as well as higher ages.