8.5

a)

```{r}
help(hodg)
data(hodg)
hodg$Z1 <- ifelse(hodg$gtype == 1 & hodg$dtype == 2, 1, 0)
hodg$Z2 <- ifelse(hodg$gtype == 2 & hodg$dtype == 1, 1, 0)
hodg$Z3 <- ifelse(hodg$gtype == 2 & hodg$dtype == 2, 1, 0)
fit <- coxph(Surv(time, delta) ~ Z1+Z2+Z3,ties = 'breslow', data = hodg)
summary(fit)
```

```
Call:
coxph(formula = Surv(time, delta) ~ Z1 + Z2 + Z3, data = hodg,
    ties = "breslow")

  n= 43, number of events= 26

     coef exp(coef) se(coef)     z Pr(>|z|)
Z1 1.8297    6.2323   0.6753 2.709  0.00674 **
Z2 0.6639    1.9423   0.5643 1.177  0.23939
Z3 0.1537    1.1662   0.5888 0.261  0.79406
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

   exp(coef) exp(-coef) lower .95 upper .95
Z1     6.232     0.1605    1.6589    23.414
Z2     1.942     0.5149    0.6427     5.870
Z3     1.166     0.8575    0.3677     3.698

Concordance= 0.605  (se = 0.058 )
Rsquare= 0.168   (max possible= 0.983 )
Likelihood ratio test= 7.89  on 3 df,   p=0.04825
Wald test            = 9.26  on 3 df,   p=0.02604
Score (logrank) test = 11.08  on 3 df,   p=0.01131
```

- Global Test :

Test	χ^2	df	p-value
LR	7.89	3	0.048
Score	11.08	3	0.011
Wald	9.26	3	0.026

- ANOVA Table :

Var	df	Est.	SE	χ^2	p-value
HOD Allo	1	1.83	0.68	7.34	0.007
NHL Auto	1	0.66	0.56	1.38	0.24
HOD Auto	1	0.15	0.59	0.07	0.79

b)

```
hodg$Z1b <- ifelse(hodg$gtype == 2, 1, 0)
hodg$Z2b <- ifelse(hodg$dtype == 2, 1, 0)
hodg$Z3b <- hodg$Z1b * hodg$Z2b
fit.hodg1 <- coxph(Surv(time, delta) ~ Z1b + Z2b + Z3b, ties = 'breslow', data = hodg)
summary(fit.hodg1)

fit.hodginter <- coxph(Surv(time, delta) ~ Z1b+Z2b, ties = 'breslow', data = hodg)
summary(fit.hodginter)
X2.lrt <- 2 * (fit.hodg1$loglik[2] - fit.hodginter$loglik[2])
1-pchisq(X2.lrt, 1)

b.null <- 0
X2.wald <- t(fit.hodg1$coefficients[3] - b.null) %*%
solve(fit.hodg1$var[3, 3]) %*%
(fit.hodg1$coefficients[3] - b.null)
1-pchisq(X2.wald, 1)
```

```
Call:
coxph(formula = Surv(time, delta) ~ Z1b + Z2b + Z3b, data = hodg,
    ties = "breslow")

  n= 43, number of events= 26

        coef exp(coef) se(coef)      z Pr(>|z|)
Z1b  0.66387   1.94229  0.56427  1.177  0.23939
Z2b  1.82974   6.23229  0.67532  2.709  0.00674 **
Z3b -2.33990   0.09634  0.85168 -2.747  0.00601 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

    exp(coef) exp(-coef) lower .95 upper .95
Z1b   1.94229     0.5149   0.64270    5.8697
Z2b   6.23229     0.1605   1.65887   23.4144
Z3b   0.09634    10.3802   0.01815    0.5114

Concordance= 0.605  (se = 0.058 )
Rsquare= 0.168   (max possible= 0.983 )
Likelihood ratio test= 7.89  on 3 df,   p=0.04825
Wald test            = 9.26  on 3 df,   p=0.02604
Score (logrank) test = 11.08  on 3 df,   p=0.01131
```

```
Call:
coxph(formula = Surv(time, delta) ~ Z1b + Z2b, data = hodg, ties = "breslow")

  n= 43, number of events= 26

       coef exp(coef) se(coef)      z Pr(>|z|)
Z1b -0.2631    0.7687   0.4457 -0.590    0.555
Z2b  0.2777    1.3200   0.4349  0.639    0.523

    exp(coef) exp(-coef) lower .95 upper .95
Z1b    0.7687     1.3010    0.3209     1.841
Z2b    1.3200     0.7575    0.5629     3.096

Concordance= 0.553  (se = 0.058 )
Rsquare= 0.012   (max possible= 0.983 )
Likelihood ratio test= 0.54  on 2 df,   p=0.7634
Wald test            = 0.53  on 2 df,   p=0.7653
Score (logrank) test = 0.54  on 2 df,   p=0.765
```

```
[1] 0.006690241
            [,1]
[1,] 0.006006927
```

← LR p-value

← Walt p-value

Both Likelihood ratio and Wald p-value are < 0.05.
Therefore, we have enough evidence to conclude that there is a signifiant interaction between disease type & transplant type

c) Relative Risk for an NHL Auto to NHL Allo of 1.94 with 95% CI (0.64, 5.87)

(d)

```
#Allo patient
C <- c(1, 0, 0)
b0 <- c(0, 0, 0)
b <- fit.hodg$coefficients
V <- fit.hodg$var
chi_allo <- t(C %*% b - C %*% b0) %*% solve(t(C) %*% V %*% C) %*% (C %*% b - C %*% b0)
pchisq(chi_allo, df=1, lower.tail = F)

#Auto patient
C <- c(0, 1, -1)
b0 <- c(0, 0, 0)
b <- fit.hodg$coefficients
V <- fit.hodg$var
chi_allo <- t(C %*% b - C %*% b0) %*% solve(t(C) %*% V %*% C) %*% (C %*% b - C %*% b0)
pchisq(chi_allo, df=1, lower.tail = F)
```

```
            [,1]
[1,] 0.006739661
         [,1]
[1,] 0.312685
```

Allo : The p-value is 0.0067

Auto : The p-value is 0.31

e)

```
C <- rbind(c(0, 1, 0), c(1, 0, -1))
b0 <- c(0, 0, 0)
b <- fit.hodg$coefficients
V <- fit.hodg$var
chi_allo <- t(C %*% b - C %*% b0) %*% solve(C %*% V %*% t(C)) %*%
(C %*% b - C %*% b0)
pchisq(chi_allo, df=2, lower.tail = F)
```

```
            [,1]
[1,] 0.01429393
```

The test Stat is 8.50, df is 2, p-value is $0.014 < 0.05$ which means statistically significant. We have enough evidence to reject H_0.

8.10

```
Call:
coxph(formula = Surv(ta, da) ~ z10, data = bmt, ties = "breslow")

        coef exp(coef) se(coef)     z    p
z10 -0.299     0.742    0.466 -0.64 0.52

Likelihood ratio test=0.43  on 1 df, p=0.51
n= 137, number of events= 26
```

a) • Cox model test the hypothesis of no difference in the rate of development of AGVHD between MTX & no MTX.

$$Z_{10} = \begin{cases} 1 & \text{with MTX} \\ 0 & \text{without MTX} \end{cases}$$

Cox model : $h(t) = h_0(t) \exp\{\beta_1 Z_{10}\}$

• Find a point estimate and a 95% C.I. for RR of AGVHD on the MTx Protocol as compare to those not given MTX

$\exp(\hat{\beta})$ Can be seen as a measure of relative risk

$$\exp(\hat{\beta}) = \frac{h(t \mid Z_1=1)}{h(t \mid Z_1=0)} = 0.742$$

$SE(\hat{\beta}) = 0.466 \Rightarrow$ se of $\exp(\hat{\beta})$

```{r}
bmt$Z1 <- ifelse(bmt$group == 1, 1, 0)
bmt$Z2 <- ifelse(bmt$group == 2, 1, 0)
bmt$Z1_MTX <- bmt$Z1 * bmt$z10
bmt$Z2_MTX <- bmt$Z2 * bmt$z10
coxph(Surv(ta, da) ~ z10 + Z1 + Z2 + Z1_MTX + Z2_MTX, data = bmt, ties = 'breslow')
```

```
Call:
coxph(formula = Surv(ta, da) ~ z10 + Z1 + Z2 + Z1_MTX + Z2_MTX,
    data = bmt, ties = "breslow")

          coef exp(coef) se(coef)     z    p
β1 z10     0.368     1.444    0.866  0.42 0.67
β2 Z1      0.821     2.273    0.646  1.27 0.20
β3 Z2      0.723     2.061    0.592  1.22 0.22
β4 Z1_MTX -0.767     0.464    1.118 -0.69 0.49
β5 Z2_MTX -1.350     0.259    1.360 -0.99 0.32

Likelihood ratio test=3.01  on 5 df, p=0.699
n= 137, number of events= 26
```

b) $Z_1 = \begin{cases} 1 & \text{ALL} \\ 0 & \text{o.w} \end{cases}$ $\quad Z_2 = \begin{cases} 1 & \text{AML High} \\ 0 & \text{o.w.} \end{cases}$

Cox model : $h(t) = h_0(t) \cdot \exp\{\beta_1 Z_1 + \beta_2 Z_2 + \beta_3 Z_{10} + \beta_4 Z_1 Z_3 + \beta_5 Z_2 Z_3\}$

$H_0: \beta_3 = 0$ $\quad p = 0.67 > 0.05$ $\quad$ not statistical significant

We don't have enough evidence to reject H_0, there's no effect of MTX on development of AGVHD, adjusting for 3 disease categories.

c) $H_0: \beta_4 = 0$ & $\beta_5 = 0$

pvalue = 0.49 & 0.32 both > 0.05 , means not statistical significant

Therefore , there's no interaction effect on AGVHD between the disease categories and use MTX .

d) Find the best model to test the primary hypo of on MTX effect on the occurrence of AGVHD

Use "MASS" Package to find best model

```{r}
bmt$Q1 <- ifelse(bmt$group == 2, 1, 0)
bmt$Q2 <- ifelse(bmt$group == 3, 1, 0)
bmt$Q3 <- bmt$z7
bmt$Q4 <- ifelse(bmt$z8 == 1, 1, 0)
bmt$Q5 <- bmt$z10
bmt$Q6 <- ifelse(bmt$z4 == 1, 1, 0)
bmt$Q7 <- ifelse(bmt$z3 == 1, 1, 0)
bmt$Q8 <- bmt$Q6 * bmt$Q7
bmt$Q9 <- ifelse(bmt$z6 == 1, 1, 0)
bmt$Q10 <-ifelse(bmt$z5 == 1, 1, 0)
bmt$Q11 <- bmt$Q9 * bmt$Q10
bmt$Q12 <- bmt$z2 - 28
bmt$Q13 <- bmt$z1 - 28
bmt$Q14 <- bmt$Q12 * bmt$Q13

fit.AIC <- coxph(Surv(ta, da) ~ Q5, data = bmt, ties = "breslow")
stepAIC(fit.AIC, direction = "both", scope = list(upper = ~ Q1 + Q2 + Q3 +Q4+Q5+Q6+Q7+Q8+Q9+Q10+Q11+Q12+Q13+Q14, lower = ~ Q5))
```

```
Call:
coxph(formula = Surv(ta, da) ~ Q5 + Q13 + Q2 + Q9, data = bmt,
    ties = "breslow")

        coef exp(coef) se(coef)     z      p
Q5   -0.5993    0.5492   0.4715 -1.27 0.2037
Q13   0.0597    1.0615   0.0216  2.76 0.0057
Q2   -0.8031    0.4479   0.4767 -1.68 0.0920
Q9    0.6686    1.9515   0.4013  1.67 0.0957

Likelihood ratio test=12.6  on 4 df, p=0.0133
n= 137, number of events= 26
```

There're 4 varibles : Q_5, Q_{13}, Q_2, Q_9 and their coefficients shown above .

8.14

a) Cox PH model : $h(t|x) = h_0(t) \cdot \exp(x^T \beta)$

Baseline : $\hat{S}_0(t) = \exp[-\hat{H}_0(t)]$

$$\hat{S}(t|x_0) = \hat{S}_0(t)^{\exp(x_0^T \hat{\beta})}$$

Result shown below :

```r
omt$X1 <- ifelse(bmt$group == 2, 1, 0)
omt$X2 <- ifelse(bmt$group == 3, 1, 0)
omt$X1_MTX <- bmt$X1 * bmt$z10
omt$X2_MTX <- bmt$X2 * bmt$z10

fit.bmt <- coxph(Surv(ta, da) ~ X1 + X2 + z10, data = bmt, ties = 'breslow')

o.haz <- basehaz(fit.bmt_14, centered = F)

t <- b.haz[ ,2]

S.est <- cbind(exp(-b.haz[,1]), t)

o.est <- fit.bmt_14$coefficients

S1_n <- S.est[,1]^(exp(t(b.est) %*% c(0, 0, 0))) # group 1 no MTX
S2_n <- S.est[,1]^(exp(t(b.est) %*% c(1, 0, 0))) # group 2 no MTX
S3_n <- S.est[,1]^(exp(t(b.est) %*% c(0, 1, 0))) # group 3 no MTX

S1 <- S.est[,1]^(exp(t(b.est) %*% c(0, 0, 1))) # group 1
S2 <- S.est[,1]^(exp(t(b.est) %*% c(1, 0, 1))) # group 2
S3 <- S.est[,1]^(exp(t(b.est) %*% c(0, 1, 1))) # group 3

res <- cbind(S1_n, S2_n, S3_n, S1, S2, S3)
colnames(res) <- c("ALL-no MTX", "AML low-no MTX", "AML high-no MTX",
                   "ALL- MTX", "AML low- MTX", "AML high- MTX")
```

	ALL-no MTX	AML low-no MTX	AML high-no MTX	ALL- MTX	AML low- MTX	AML high- MTX
[1,]	1.0000000	1.0000000	1.0000000	1.0000000	1.0000000	1.0000000
[2,]	1.0000000	1.0000000	1.0000000	1.0000000	1.0000000	1.0000000
[3,]	0.9796302	0.9826000	0.9889675	0.9856627	0.9877585	0.9922457
[4,]	0.9694026	0.9738436	0.9833883	0.9784305	0.9815737	0.9883145
[5,]	0.9591325	0.9650371	0.9777586	0.9711454	0.9753367	0.9843409
[6,]	0.9488786	0.9562306	0.9721099	0.9638484	0.9690827	0.9803471

b) 95% C.I. for survival function of AML High Risk patient at 80 days with no MTX :

```
Call: survfit(formula = fit.bmt, newdata = data.frame(Q1 = 0, Q2 = 1,
    z10 = 0), se.fit = TRUE, conf.int = 0.95)
```

time	n.risk	n.event	survival	std.err	lower 95% CI	upper 95% CI
10	135	2	0.989	0.00877	0.972	1.000
16	132	1	0.983	0.01131	0.961	1.000
18	130	1	0.978	0.01369	0.951	1.000
20	129	1	0.972	0.01597	0.941	1.000
21	128	3	0.955	0.02240	0.912	1.000
22	125	1	0.950	0.02450	0.903	0.999
25	124	2	0.938	0.02863	0.884	0.996
28	122	2	0.927	0.03267	0.865	0.993
29	120	2	0.915	0.03667	0.846	0.990
30	118	1	0.909	0.03866	0.837	0.988
32	117	1	0.903	0.04063	0.827	0.987
36	115	1	0.898	0.04260	0.818	0.985
38	114	2	0.886	0.04649	0.799	0.982
39	112	1	0.880	0.04841	0.790	0.980
52	110	1	0.874	0.05033	0.781	0.978
67	107	1	0.868	0.05227	0.771	0.977
70	106	1	0.862	0.05421	0.762	0.975
72	105	1	0.856	0.05613	0.752	0.973
88	102	1	0.849	0.05807	0.743	0.971

$S(80) = 0.856$, 95% CI : $(0.752, 0.973)$

95% C.I. for survival function of AML High Risk patient at 80 days with MTX :

```
Call: survfit(formula = fit.bmt, newdata = data.frame(Q1 = 0, Q2 = 1,
    z10 = 1), se.fit = TRUE, conf.int = 0.95)
```

time	n.risk	n.event	survival	std.err	lower 95% CI	upper 95% CI
10	135	2	0.992	0.00680	0.979	1
16	132	1	0.988	0.00907	0.971	1
18	130	1	0.984	0.01127	0.962	1
20	129	1	0.980	0.01343	0.954	1
21	128	3	0.968	0.01973	0.930	1
22	125	1	0.964	0.02182	0.922	1
25	124	2	0.956	0.02596	0.907	1
28	122	2	0.948	0.03008	0.891	1
29	120	2	0.940	0.03418	0.875	1
30	118	1	0.935	0.03624	0.867	1
32	117	1	0.931	0.03829	0.859	1
36	115	1	0.927	0.04035	0.851	1
38	114	2	0.918	0.04446	0.835	1
39	112	1	0.914	0.04652	0.827	1
52	110	1	0.910	0.04860	0.819	1
67	107	1	0.905	0.05073	0.811	1
70	106	1	0.901	0.05285	0.803	1
72	105	1	0.896	0.05496	0.795	1
88	102	1	0.892	0.05712	0.787	1

$S(80) = 0.896$, 95% C.I. : $(0.795, 1)$

9.1 Effect of ploidy on survival for patients with cancer of tongue.

$Z_2(t)$: fixed time covariate of intrest. $Z_2(t) = Z_1 \times g(t)$

$H_0: \beta_2 = 0$

Test for the proportional hazard function.

$Z_1 = \begin{cases} 1 & \text{Aneuploid} \\ 0 & \text{Diploid} \end{cases}$ $\quad Z_2 = Z_1 \cdot \log(\text{time})$

```
help("tongue")
data(tongue)
cut.points <- unique(tongue$time[tongue$delta == 1])
tongue1 <- survSplit(data = tongue, cut = cut.points, end = "time", start = "t0", event = "delta")

tongue1$X1 <- ifelse(tongue1$type == 2 , 1, 0)
tongue1$X2 <- tongue1$X1 * log(tongue1$time)
fit.tongue <- coxph(Surv(t0, time, delta) ~ X1 + X2, data = tongue1, ties = 'breslow')
summary(fit.tongue)
```

```
Call:
coxph(formula = Surv(t0, time, delta) ~ X1 + X2, data = tongue1,
    ties = "breslow")

  n= 1808, number of events= 53

      coef exp(coef) se(coef)      z Pr(>|z|)
X1  0.9718    2.6427   0.7580  1.282    0.200
X2 -0.1557    0.8558   0.2148 -0.725    0.469

   exp(coef) exp(-coef) lower .95 upper .95
X1    2.6427     0.3784    0.5982    11.674
X2    0.8558     1.1685    0.5618     1.304

Concordance= 0.564  (se = 0.036 )
Rsquare= 0.002   (max possible= 0.197 )
Likelihood ratio test= 3.14  on 2 df,   p=0.2078
Wald test            = 3.2  on 2 df,   p=0.2014
Score (logrank) test = 3.33  on 2 df,   p=0.1895
```

> 0.05

P-values > 0.05, which means statistically insignificant. So we don't have evidence to reject H_0. We conclude that the hazard rates for two groups are proportional.

9.3

a)

```
fit.ct <- coxph(Surv(time, delta) ~ group, data = data, ties = "breslow")

summary(fit.ct)
```

```
Call:
coxph(formula = Surv(time, delta) ~ group, data = data, ties = "breslow")

  n= 90, number of events= 82

          coef exp(coef) se(coef)      z Pr(>|z|)
group -0.1075    0.8981   0.2234 -0.481     0.63

      exp(coef) exp(-coef) lower .95 upper .95
group    0.8981      1.113    0.5797     1.391

Concordance= 0.562  (se = 0.031 )
Rsquare= 0.003   (max possible= 0.999 )
Likelihood ratio test= 0.23  on 1 df,   p=0.6308
Wald test            = 0.23  on 1 df,   p=0.6304
Score (logrank) test = 0.23  on 1 df,   p=0.6303
```

Relative Risk = 0.8981 , 95% C.I of RR = (0.5797, 1.391)

b)

```
cut.points_non <- unique(data$time[data$delta == 1])
data1 <- survSplit(data = data, cut = cut.points_non, end = "time", start = "t0", event = "delta")
data1$X1 <- data1$group * log(data1$time)
fit.non <- coxph(Surv(t0, time, delta) ~ group + X1, data = data1, ties = 'breslow')
summary(fit.non)
```

```
Call:
coxph(formula = Surv(t0, time, delta) ~ group + X1, data = data1,
    ties = "breslow")

  n= 3960, number of events= 82

         coef exp(coef) se(coef)     z Pr(>|z|)
group -3.8727    0.0208   1.4782 -2.62  0.00879 **
X1     0.6475    1.9108   0.2481  2.61  0.00906 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

      exp(coef) exp(-coef) lower .95 upper .95
group    0.0208    48.0722  0.001148     0.377
X1       1.9108     0.5233  1.174937     3.107

Concordance= 0.575  (se = 0.031 )
Rsquare= 0.002   (max possible= 0.144 )
Likelihood ratio test= 8.56  on 2 df,   p=0.01384
Wald test            = 6.88  on 2 df,   p=0.032
Score (logrank) test = 7.6  on 2 df,   p=0.02237
```

Walt p-value for X_1 is 0.00906 , < 0.05 .

c)

```
loglik <- as.numeric(length(cut.points_non))
for(i in 1:length(cut.points_non)){
data1$tdc1 <- ifelse(data1$time > cut.points_non[i], data1$group, 0)
fit.tdc <- coxph(Surv(t0, time, delta) ~ group + tdc1, data = data1, ties = 'breslow')
loglik[i] <- fit.tdc$loglik[2]
}
# cbind(cut.points_non, loglik)
opt_tau <- cut.points_non[which.max(loglik)]
opt_tau
```

```
Loglik converged before variable  1,2 ; beta may be infinite. X matrix deemed to be si
converged before variable  2 ; beta may be infinite. [1] 254
```

The cutpoint is at 254 days

```r
data(larynx)
help(larynx)
#Create dummy variables for stage variable (s2, s3, s4)
larynx$s2 <- ifelse(larynx$stage == 2, 1, 0)
larynx$s3 <- ifelse(larynx$stage == 3, 1, 0)
larynx$s4 <- ifelse(larynx$stage == 4, 1, 0)
larynx$yr <- ifelse(larynx$diagyr < 75, 1, 0)

cut.points <- unique(larynx$time[larynx$delta == 1])
larynx1 <- survSplit(data = larynx, cut = cut.points, end = "time", start = "t0", event = "delta")
# stratify based on year
fit <- coxph(Surv(t0, time, delta) ~ s2+s3+s4+age+strata(yr), data = larynx1, ties = 'breslow')
fit
```

ANOVA Table Shown as below:

```
Call:
coxph(formula = Surv(t0, time, delta) ~ s2 + s3 + s4 + age +
    strata(yr), data = larynx1, ties = "breslow")

      coef exp(coef) se(coef)    z       p
s2  0.1122    1.1187   0.4641 0.24 0.80904
s3  0.6195    1.8580   0.3560 1.74 0.08181
s4  1.6970    5.4575   0.4403 3.85 0.00012
age 0.0170    1.0171   0.0149 1.14 0.25488

Likelihood ratio test=17.6  on 4 df, p=0.00149
n= 1919, number of events= 50
```

b)

```r
larynx_yr0 <- larynx1[larynx1$yr == 0, ]
larynx_yr1 <- larynx1[larynx1$yr == 1, ]
fit0 <- coxph(Surv(t0, time, delta) ~ s2+s3+s4+age, data = larynx_yr0, ties = 'breslow')

fit1 <- coxph(Surv(t0, time, delta) ~ s2+s3+s4+age, data = larynx_yr1, ties = 'breslow')

#LR
X2 <- -2*(fit$loglik[2] - (fit0$loglik[2] + fit1$loglik[2])); X2
1 - pchisq(X2, 4)
```

LR test statistics $\chi^2 = 3.062836$ P-value = 0.5473

c)

```r
W1 <- (fit0$coefficients[1] - fit1$coefficients[1])^2 / (fit1$var[1,1] + fit0$var[1,1]); W1
1 - pchisq(W1, 1) #p-value

W2 <- (fit0$coefficients[2] - fit1$coefficients[2])^2 / (fit1$var[2,2] + fit0$var[2,2]); W2
1 - pchisq(W2, 1) #p-value

W3 <- (fit0$coefficients[3] - fit1$coefficients[3])^2 / (fit1$var[3,3] + fit0$var[3,3]); W3
1 - pchisq(W3, 1) #p-value

W4 <- (fit0$coefficients[4] - fit1$coefficients[4])^2 / (fit1$var[4,4] + fit0$var[4,4]); W4
1 - pchisq(W4, 1) #p-value
```

Individual Walt Test

```r
C <-rbind(c(1, 0, 0, 0), c(0, 1, 0, 0), c(0, 0, 1, 0), c(0, 0, 0, 1))
b0 <-fit0$coefficients
b1 <- fit1$coefficients
V <- fit0$var + fit1$var
wald <- t(b1 - b0) %*% solve(C %*% V %*% t(C)) %*% (b1 - b0)

wald
1- pchisq(wald, 4)
```

Overall walt test

Walt test stat $\chi^2 = 2.82$, P-value = 0.59

9.8.

a)

```
cut.points <- unique(burn$T3[burn$D3 == 1])

burn1 <- survSplit(data = burn, cut = cut.points, end = "T3", start = "t0", event = "D3")

#Create time-dependent covariates
burn1$co <- ifelse(burn1$T3 >= burn1$T1 & burn1$D1 == 1, 1, 0)
```
← Covariate

```
fit <- coxph(Surv(t0, T3, D3) ~ co, data = burn1, ties = 'breslow')
summary(fit)
```

```
Call:
coxph(formula = Surv(t0, T3, D3) ~ co, data = burn1, ties = "breslow")

  n= 2265, number of events= 48

      coef exp(coef) se(coef)      z Pr(>|z|)
co -0.8699    0.4190   0.4386 -1.983   0.0473 *
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

   exp(coef) exp(-coef) lower .95 upper .95
co     0.419      2.387    0.1773    0.9899

Concordance= 0.559  (se = 0.029 )
Rsquare= 0.002   (max possible= 0.176 )
Likelihood ratio test= 4.27  on 1 df,   p=0.03882
Wald test            = 3.93  on 1 df,   p=0.04735
Score (logrank) test = 4.01  on 1 df,   p=0.04516
```

b)

```{r}
burn1$co1 <- ifelse(burn1$T3 >= burn1$T2 & burn1$D2 == 1, 1, 0)

fit1 <- coxph(Surv(t0, T3, D3) ~ co1, data = burn1, ties = 'breslow')
```
← another covariate

```
summary(fit1)
```

```
Call:
coxph(formula = Surv(t0, T3, D3) ~ co1, data = burn1, ties = "breslow")

  n= 2265, number of events= 48

       coef exp(coef) se(coef)      z Pr(>|z|)
co1 -0.2162    0.8056   0.3537 -0.611    0.541

    exp(coef) exp(-coef) lower .95 upper .95
co1    0.8056      1.241    0.4028     1.611

Concordance= 0.519  (se = 0.031 )
Rsquare= 0   (max possible= 0.176 )
Likelihood ratio test= 0.38  on 1 df,   p=0.5364
Wald test            = 0.37  on 1 df,   p=0.541
Score (logrank) test = 0.37  on 1 df,   p=0.5405
```

c)

```
burn1$Z1_logt <- burn1$Z1 * log(burn1$T3)
burn1$Z2_logt <- burn1$Z2 * log(burn1$T3)
burn1$Z3_logt <- burn1$Z3 * log(burn1$T3)
burn1$Z4_logt <- burn1$Z4 * log(burn1$T3)
burn1$Z5_logt <- burn1$Z5 * log(burn1$T3)
burn1$Z6_logt <- burn1$Z6 * log(burn1$T3)
burn1$Z7_logt <- burn1$Z7 * log(burn1$T3)
burn1$Z8_logt <- burn1$Z8 * log(burn1$T3)
burn1$Z9_logt <- burn1$Z9 * log(burn1$T3)
burn1$Z10_logt <- burn1$Z10 * log(burn1$T3)
burn1$co_logt <- burn1$co * log(burn1$T3)
burn1$co1_logt <- burn1$co1 * log(burn1$T3)
burn1$Z11_1 <- ifelse(burn1$Z11 == 2, 1, 0)
burn1$Z11_2 <- ifelse(burn1$Z11 == 3, 1, 0)
burn1$Z11_3 <- ifelse(burn1$Z11 == 4, 1, 0)
burn1$Z11_1_logt <- burn1$Z11_1 * log(burn1$T3)
burn1$Z11_2_logt <- burn1$Z11_2 * log(burn1$T3)
burn1$Z11_3_logt <- burn1$Z11_3 * log(burn1$T3)
fit.burn_1 <- coxph(Surv(t0, T3, D3) ~  Z1+Z2+Z3+Z4+Z5+Z6+Z7+Z8+Z9+Z10+factor(Z11)+co+co1+Z9_logt, data = burn1, ties =
'breslow')
summary(fit.burn_1)
fit.burn_2 <- coxph(Surv(t0, T3, D3) ~  Z1+Z2+Z3+Z4+Z5+Z6+Z7+Z8+Z9+Z10+factor(Z11)+co+co1+Z11_1_logt, data = burn1,
ties = 'breslow')
summary(fit.burn_2)
fit.burn_3 <- coxph(Surv(t0, T3, D3) ~  Z1+Z2+Z3+Z4+Z5+Z6+Z7+Z8+Z9+Z10+factor(Z11)+co+co1+Z11_3_logt, data = burn1,
ties = 'breslow')
summary(fit.burn_3)
```

I attached R markdown file for this question

The result was super long. The result showed that Z9, Z11(2) & Z11(4) are non-propotional hazard.

Then, we fit $2^3 = 8$ Cox's models. Then, we use LR test to test whether the covariate effect of each stratified variable is the same.

d)

```{r}
burn2 <- burn[burn$D2==1,]
cut.points <- unique(burn2$T3[burn2$D3 == 1])
burn3 <- survSplit(data = burn2, cut = cut.points, end = "T3", start = "t0", event = "D3")
burn3$Z1_logt <- burn3$Z1 * log(burn3$T3)
burn3$Z2_logt <- burn3$Z2 * log(burn3$T3)
burn3$Z3_logt <- burn3$Z3 * log(burn3$T3)
burn3$Z4_logt <- burn3$Z4 * log(burn3$T3)
burn3$Z5_logt <- burn3$Z5 * log(burn3$T3)
burn3$Z6_logt <- burn3$Z6 * log(burn3$T3)
burn3$Z7_logt <- burn3$Z7 * log(burn3$T3)
burn3$Z8_logt <- burn3$Z8 * log(burn3$T3)
burn3$Z9_logt <- burn3$Z9 * log(burn3$T3)
burn3$Z10_logt <- burn3$Z10 * log(burn3$T3)
burn3$Z11_1 <- ifelse(burn3$Z11 == 2, 1, 0)
burn3$Z11_2 <- ifelse(burn3$Z11 == 3, 1, 0)
burn3$Z11_3 <- ifelse(burn3$Z11 == 4, 1, 0)
burn3$Z11_1_logt <- burn3$Z11_1 * log(burn3$T3)
burn3$Z11_2_logt <- burn3$Z11_2 * log(burn3$T3)
burn3$Z11_3_logt <- burn3$Z11_3 * log(burn3$T3)
burn3$X1 <- ifelse(burn3$T3 >= burn3$T1 & burn3$D1 == 1, 1, 0)
burn3$X2 <- ifelse(burn3$T3 >= burn3$T2 & burn3$D2 == 1, 1, 0)
burn3$X1_logt <- burn3$X1 * log(burn3$T3)
burn3$X2_logt <- burn3$X2 * log(burn3$T3)
fit.burn_4 <- coxph(Surv(t0, T3, D3) ~  Z1+Z2+Z3+Z4+Z5+Z6+Z7+Z8+Z9+Z10+factor(Z11)+X1+X2+Z11_3_logt, data = burn3, ties
= 'breslow')
summary(fit.burn_4)
```

P-value for each variable multiplied by log(3) > 0.05.

There's no non-proportional variable need adjusting.

```
burn1$Z1_logt <- burn1$Z1 * log(burn1$T3)
burn1$Z2_logt <- burn1$Z2 * log(burn1$T3)
burn1$Z3_logt <- burn1$Z3 * log(burn1$T3)
burn1$Z4_logt <- burn1$Z4 * log(burn1$T3)
burn1$Z5_logt <- burn1$Z5 * log(burn1$T3)
burn1$Z6_logt <- burn1$Z6 * log(burn1$T3)
burn1$Z7_logt <- burn1$Z7 * log(burn1$T3)
burn1$Z8_logt <- burn1$Z8 * log(burn1$T3)
burn1$Z9_logt <- burn1$Z9 * log(burn1$T3)
burn1$Z10_logt <- burn1$Z10 * log(burn1$T3)
burn1$X1_logt <- burn1$X1 * log(burn1$T3)
burn1$X2_logt <- burn1$X2 * log(burn1$T3)
burn1$Z11_1 <- ifelse(burn1$Z11 == 2, 1, 0)
burn1$Z11_2 <- ifelse(burn1$Z11 == 3, 1, 0)
burn1$Z11_3 <- ifelse(burn1$Z11 == 4, 1, 0)
burn1$Z11_1_logt <- burn1$Z11_1 * log(burn1$T3)
burn1$Z11_2_logt <- burn1$Z11_2 * log(burn1$T3)
burn1$Z11_3_logt <- burn1$Z11_3 * log(burn1$T3)
fit.burn_1 <- coxph(Surv(t0, T3, D3) ~  Z1+Z2+Z3+Z4+Z5+Z6+Z7+Z8+Z9+Z10+factor
(Z11)+X1+X2+Z9_logt, data = burn1, ties = 'breslow')
summary(fit.burn_1)

## Call:
## coxph(formula = Surv(t0, T3, D3) ~ Z1 + Z2 + Z3 + Z4 + Z5 + Z6 +
##     Z7 + Z8 + Z9 + Z10 + factor(Z11) + X1 + X2 + Z9_logt, data = burn1,
##     ties = "breslow")
##
##   n= 2265, number of events= 48
##
##                     coef exp(coef)  se(coef)      z Pr(>|z|)
## Z1             -0.512046  0.599268  0.332452 -1.540   0.1235
## Z2             -0.533575  0.586505  0.409061 -1.304   0.1921
## Z3              2.232432  9.322512  1.041671  2.143   0.0321 *
## Z4              0.002227  1.002230  0.009750  0.228   0.8193
## Z5             -0.027148  0.973217  0.373909 -0.073   0.9421
## Z6              0.593789  1.810837  0.430185  1.380   0.1675
## Z7             -0.087971  0.915787  0.510760 -0.172   0.8633
## Z8             -0.161386  0.850964  0.390017 -0.414   0.6790
## Z9              1.187825  3.279940  0.814180  1.459   0.1446
## Z10             0.262749  1.300501  0.379058  0.693   0.4882
## factor(Z11)2    1.483047  4.406350  1.125233  1.318   0.1875
## factor(Z11)3    2.014883  7.499853  1.144508  1.760   0.0783 .
## factor(Z11)4    0.815790  2.260961  1.047933  0.778   0.4363
## X1             -0.656238  0.518800  0.488373 -1.344   0.1790
## X2             -0.111971  0.894070  0.381398 -0.294   0.7691
## Z9_logt        -0.769492  0.463248  0.385125 -1.998   0.0457 *
```

```
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##                exp(coef) exp(-coef) lower .95 upper .95
## Z1                0.5993     1.6687    0.3123    1.1498
## Z2                0.5865     1.7050    0.2631    1.3076
## Z3                9.3225     0.1073    1.2102   71.8133
## Z4                1.0022     0.9978    0.9833    1.0216
## Z5                0.9732     1.0275    0.4677    2.0253
## Z6                1.8108     0.5522    0.7793    4.2078
## Z7                0.9158     1.0920    0.3365    2.4920
## Z8                0.8510     1.1751    0.3962    1.8277
## Z9                3.2799     0.3049    0.6650   16.1770
## Z10               1.3005     0.7689    0.6187    2.7338
## factor(Z11)2      4.4063     0.2269    0.4856   39.9834
## factor(Z11)3      7.4999     0.1333    0.7959   70.6741
## factor(Z11)4      2.2610     0.4423    0.2899   17.6317
## X1                0.5188     1.9275    0.1992    1.3511
## X2                0.8941     1.1185    0.4234    1.8881
## Z9_logt           0.4632     2.1587    0.2178    0.9854
##
## Concordance= 0.742  (se = 0.046 )
## Rsquare= 0.014   (max possible= 0.176 )
## Likelihood ratio test= 33  on 16 df,   p=0.007398
## Wald test            = 26.54  on 16 df,   p=0.04695
## Score (logrank) test = 30.57  on 16 df,   p=0.01527
```

```
fit.burn_2 <- coxph(Surv(t0, T3, D3) ~  Z1+Z2+Z3+Z4+Z5+Z6+Z7+Z8+Z9+Z10+factor
(Z11)+X1+X2+Z11_1_logt, data = burn1, ties = 'breslow')
summary(fit.burn_2)
```

```
## Call:
## coxph(formula = Surv(t0, T3, D3) ~ Z1 + Z2 + Z3 + Z4 + Z5 + Z6 +
##     Z7 + Z8 + Z9 + Z10 + factor(Z11) + X1 + X2 + Z11_1_logt,
##     data = burn1, ties = "breslow")
##
##   n= 2265, number of events= 48
##
##                   coef exp(coef)  se(coef)      z Pr(>|z|)
## Z1           -0.611424  0.542578  0.334821 -1.826   0.0678 .
## Z2           -0.517405  0.596065  0.408518 -1.267   0.2053
## Z3            2.107986  8.231642  1.035470  2.036   0.0418 *
## Z4            0.002824  1.002828  0.009747  0.290   0.7720
## Z5           -0.091639  0.912435  0.370390 -0.247   0.8046
## Z6            0.602352  1.826409  0.431211  1.397   0.1624
## Z7            0.012729  1.012810  0.510874  0.025   0.9801
## Z8           -0.202155  0.816968  0.395273 -0.511   0.6090
## Z9           -0.276036  0.758785  0.368864 -0.748   0.4543
## Z10           0.259425  1.296185  0.379265  0.684   0.4940
## factor(Z11)2  3.391876 29.721663  1.445321  2.347   0.0189 *
```

```
## factor(Z11)3  2.115241  8.291582  1.146546  1.845   0.0651 .
## factor(Z11)4  0.866786  2.379252  1.051673  0.824   0.4098
## X1           -0.618331  0.538843  0.486884 -1.270   0.2041
## X2           -0.046297  0.954759  0.379345 -0.122   0.9029
## Z11_1_logt   -1.109465  0.329735  0.565092 -1.963   0.0496 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##              exp(coef) exp(-coef) lower .95 upper .95
## Z1              0.5426    1.84305    0.2815    1.0458
## Z2              0.5961    1.67767    0.2676    1.3275
## Z3              8.2316    0.12148    1.0817   62.6440
## Z4              1.0028    0.99718    0.9839    1.0222
## Z5              0.9124    1.09597    0.4415    1.8857
## Z6              1.8264    0.54752    0.7844    4.2525
## Z7              1.0128    0.98735    0.3721    2.7567
## Z8              0.8170    1.22404    0.3765    1.7728
## Z9              0.7588    1.31790    0.3682    1.5635
## Z10             1.2962    0.77149    0.6164    2.7258
## factor(Z11)2   29.7217    0.03365    1.7491  505.0482
## factor(Z11)3    8.2916    0.12060    0.8764   78.4476
## factor(Z11)4    2.3793    0.42030    0.3029   18.6907
## X1              0.5388    1.85583    0.2075    1.3993
## X2              0.9548    1.04738    0.4539    2.0081
## Z11_1_logt      0.3297    3.03274    0.1089    0.9981
##
## Concordance= 0.75  (se = 0.046 )
## Rsquare= 0.015   (max possible= 0.176 )
## Likelihood ratio test= 33.45  on 16 df,   p=0.006437
## Wald test            = 28.39  on 16 df,   p=0.02838
## Score (logrank) test = 32.7  on 16 df,   p=0.008099
```

```
fit.burn_3 <- coxph(Surv(t0, T3, D3) ~  Z1+Z2+Z3+Z4+Z5+Z6+Z7+Z8+Z9+Z10+factor
(Z11)+X1+X2+Z11_3_logt, data = burn1, ties = 'breslow')
summary(fit.burn_3)
```

```
## Call:
## coxph(formula = Surv(t0, T3, D3) ~ Z1 + Z2 + Z3 + Z4 + Z5 + Z6 +
##     Z7 + Z8 + Z9 + Z10 + factor(Z11) + X1 + X2 + Z11_3_logt,
##     data = burn1, ties = "breslow")
##
##   n= 2265, number of events= 48
##
##                   coef exp(coef)  se(coef)      z Pr(>|z|)
## Z1           -0.619562  0.538180  0.332304 -1.864   0.0623 .
## Z2           -0.538179  0.583810  0.408731 -1.317   0.1879
## Z3            2.150549  8.589573  1.035625  2.077   0.0378 *
## Z4            0.002803  1.002807  0.009736  0.288   0.7734
## Z5           -0.057916  0.943729  0.369671 -0.157   0.8755
## Z6            0.600562  1.823143  0.431758  1.391   0.1642
```

```
## Z7           -0.018792  0.981383  0.510207 -0.037   0.9706
## Z8           -0.209377  0.811089  0.392949 -0.533   0.5941
## Z9           -0.286154  0.751147  0.365956 -0.782   0.4343
## Z10           0.254382  1.289665  0.379729  0.670   0.5029
## factor(Z11)2  1.274127  3.575580  1.122947  1.135   0.2565
## factor(Z11)3  1.694910  5.446155  1.139273  1.488   0.1368
## factor(Z11)4 -1.526701  0.217251  1.418293 -1.076   0.2817
## X1           -0.668221  0.512620  0.482212 -1.386   0.1658
## X2           -0.026358  0.973986  0.377121 -0.070   0.9443
## Z11_3_logt    1.189838  3.286548  0.516537  2.303   0.0213 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##              exp(coef) exp(-coef) lower .95 upper .95
## Z1              0.5382     1.8581   0.28059     1.032
## Z2              0.5838     1.7129   0.26203     1.301
## Z3              8.5896     0.1164   1.12835    65.388
## Z4              1.0028     0.9972   0.98385     1.022
## Z5              0.9437     1.0596   0.45728     1.948
## Z6              1.8231     0.5485   0.78218     4.249
## Z7              0.9814     1.0190   0.36104     2.668
## Z8              0.8111     1.2329   0.37548     1.752
## Z9              0.7511     1.3313   0.36663     1.539
## Z10             1.2897     0.7754   0.61270     2.715
## factor(Z11)2    3.5756     0.2797   0.39581    32.300
## factor(Z11)3    5.4462     0.1836   0.58390    50.797
## factor(Z11)4    0.2173     4.6030   0.01348     3.501
## X1              0.5126     1.9508   0.19922     1.319
## X2              0.9740     1.0267   0.46510     2.040
## Z11_3_logt      3.2865     0.3043   1.19416     9.045
##
## Concordance= 0.754  (se = 0.046 )
## Rsquare= 0.016   (max possible= 0.176 )
## Likelihood ratio test= 35.5  on 16 df,   p=0.003394
## Wald test            = 28.68  on 16 df,   p=0.0262
## Score (logrank) test = 34.64  on 16 df,   p=0.004448
```

```
burn2 <- burn[burn$D2==1,]
cut.points <- unique(burn2$T3[burn2$D3 == 1])
burn3 <- survSplit(data = burn2, cut = cut.points, end = "T3", start = "t0",
event = "D3")
burn3$Z1_logt <- burn3$Z1 * log(burn3$T3)
burn3$Z2_logt <- burn3$Z2 * log(burn3$T3)
burn3$Z3_logt <- burn3$Z3 * log(burn3$T3)
burn3$Z4_logt <- burn3$Z4 * log(burn3$T3)
burn3$Z5_logt <- burn3$Z5 * log(burn3$T3)
burn3$Z6_logt <- burn3$Z6 * log(burn3$T3)
burn3$Z7_logt <- burn3$Z7 * log(burn3$T3)
burn3$Z8_logt <- burn3$Z8 * log(burn3$T3)
burn3$Z9_logt <- burn3$Z9 * log(burn3$T3)
```

```r
burn3$Z10_logt <- burn3$Z10 * log(burn3$T3)
burn3$Z11_1 <- ifelse(burn3$Z11 == 2, 1, 0)
burn3$Z11_2 <- ifelse(burn3$Z11 == 3, 1, 0)
burn3$Z11_3 <- ifelse(burn3$Z11 == 4, 1, 0)
burn3$Z11_1_logt <- burn3$Z11_1 * log(burn3$T3)
burn3$Z11_2_logt <- burn3$Z11_2 * log(burn3$T3)
burn3$Z11_3_logt <- burn3$Z11_3 * log(burn3$T3)
burn3$X1 <- ifelse(burn3$T3 >= burn3$T1 & burn3$D1 == 1, 1, 0)
burn3$X2 <- ifelse(burn3$T3 >= burn3$T2 & burn3$D2 == 1, 1, 0)
burn3$X1_logt <- burn3$X1 * log(burn3$T3)
burn3$X2_logt <- burn3$X2 * log(burn3$T3)
fit.burn_4 <- coxph(Surv(t0, T3, D3) ~  Z1+Z2+Z3+Z4+Z5+Z6+Z7+Z8+Z9+Z10+factor
(Z11)+X1+X2+Z11_3_logt, data = burn3, ties = 'breslow')
```

```
## Warning in fitter(X, Y, strats, offset, init, control, weights = weights,
:
## Loglik converged before variable 11,12,15 ; beta may be infinite.
```

```r
summary(fit.burn_4)
```

```
## Call:
## coxph(formula = Surv(t0, T3, D3) ~ Z1 + Z2 + Z3 + Z4 + Z5 + Z6 +
##     Z7 + Z8 + Z9 + Z10 + factor(Z11) + X1 + X2 + Z11_3_logt,
##     data = burn3, ties = "breslow")
##
##   n= 590, number of events= 14
##
##                     coef  exp(coef)   se(coef)      z Pr(>|z|)
## Z1            -3.530e-01  7.026e-01  6.206e-01 -0.569   0.5695
## Z2             1.462e-01  1.157e+00  6.477e-01  0.226   0.8215
## Z3            -2.898e-01  7.484e-01  1.168e+00 -0.248   0.8040
## Z4            -2.583e-02  9.745e-01  2.098e-02 -1.231   0.2184
## Z5             1.405e+00  4.074e+00  9.209e-01  1.525   0.1272
## Z6             2.725e+00  1.526e+01  1.135e+00  2.401   0.0163 *
## Z7             4.842e-01  1.623e+00  1.497e+00  0.323   0.7465
## Z8            -3.889e-01  6.778e-01  1.034e+00 -0.376   0.7069
## Z9            -9.674e-01  3.801e-01  8.259e-01 -1.171   0.2414
## Z10            5.629e-01  1.756e+00  6.965e-01  0.808   0.4189
## factor(Z11)2 -2.009e+01  1.888e-09  1.216e+04 -0.002   0.9987
## factor(Z11)3 -1.772e+01  2.006e-08  2.687e+04 -0.001   0.9995
## factor(Z11)4  6.687e+00  8.021e+02  1.866e+01  0.358   0.7201
## X1            -1.113e+00  3.284e-01  9.277e-01 -1.200   0.2301
## X2             2.082e+01  1.100e+09  1.010e+04  0.002   0.9984
## Z11_3_logt    -2.362e+00  9.421e-02  6.461e+00 -0.366   0.7146
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##               exp(coef) exp(-coef) lower .95 upper .95
## Z1            7.026e-01  1.423e+00 2.082e-01 2.371e+00
## Z2            1.157e+00  8.640e-01 3.252e-01 4.119e+00
```

```
## Z3           7.484e-01  1.336e+00 7.590e-02 7.380e+00
## Z4           9.745e-01  1.026e+00 9.352e-01 1.015e+00
## Z5           4.074e+00  2.455e-01 6.701e-01 2.477e+01
## Z6           1.526e+01  6.554e-02 1.650e+00 1.411e+02
## Z7           1.623e+00  6.162e-01 8.623e-02 3.054e+01
## Z8           6.778e-01  1.475e+00 8.929e-02 5.145e+00
## Z9           3.801e-01  2.631e+00 7.531e-02 1.918e+00
## Z10          1.756e+00  5.695e-01 4.484e-01 6.876e+00
## factor(Z11)2 1.888e-09  5.297e+08 0.000e+00       Inf
## factor(Z11)3 2.006e-08  4.986e+07 0.000e+00       Inf
## factor(Z11)4 8.021e+02  1.247e-03 1.046e-13 6.151e+18
## X1           3.284e-01  3.045e+00 5.330e-02 2.024e+00
## X2           1.100e+09  9.089e-10 0.000e+00       Inf
## Z11_3_logt   9.421e-02  1.061e+01 2.984e-07 2.974e+04
##
## Concordance= 0.89  (se = 0.086 )
## Rsquare= 0.05   (max possible= 0.158 )
## Likelihood ratio test= 30.38  on 16 df,   p=0.01615
## Wald test            = 11.99  on 16 df,   p=0.7449
## Score (logrank) test = 25.18  on 16 df,   p=0.06672
```