

## veteran dataset

We will still use veteran data set in `survival` package from Veterans' Administration Lung Cancer study.

```
head(veteran)
```

##	trt	celltype	time	status	karno	diagtime	age	prior
## 1	1	squamous	72	1	60	7	69	0
## 2	1	squamous	411	1	70	5	64	10
## 3	1	squamous	228	1	60	3	38	0
## 4	1	squamous	126	1	60	9	63	10
## 5	1	squamous	118	1	70	11	65	10
## 6	1	squamous	10	1	20	5	49	0

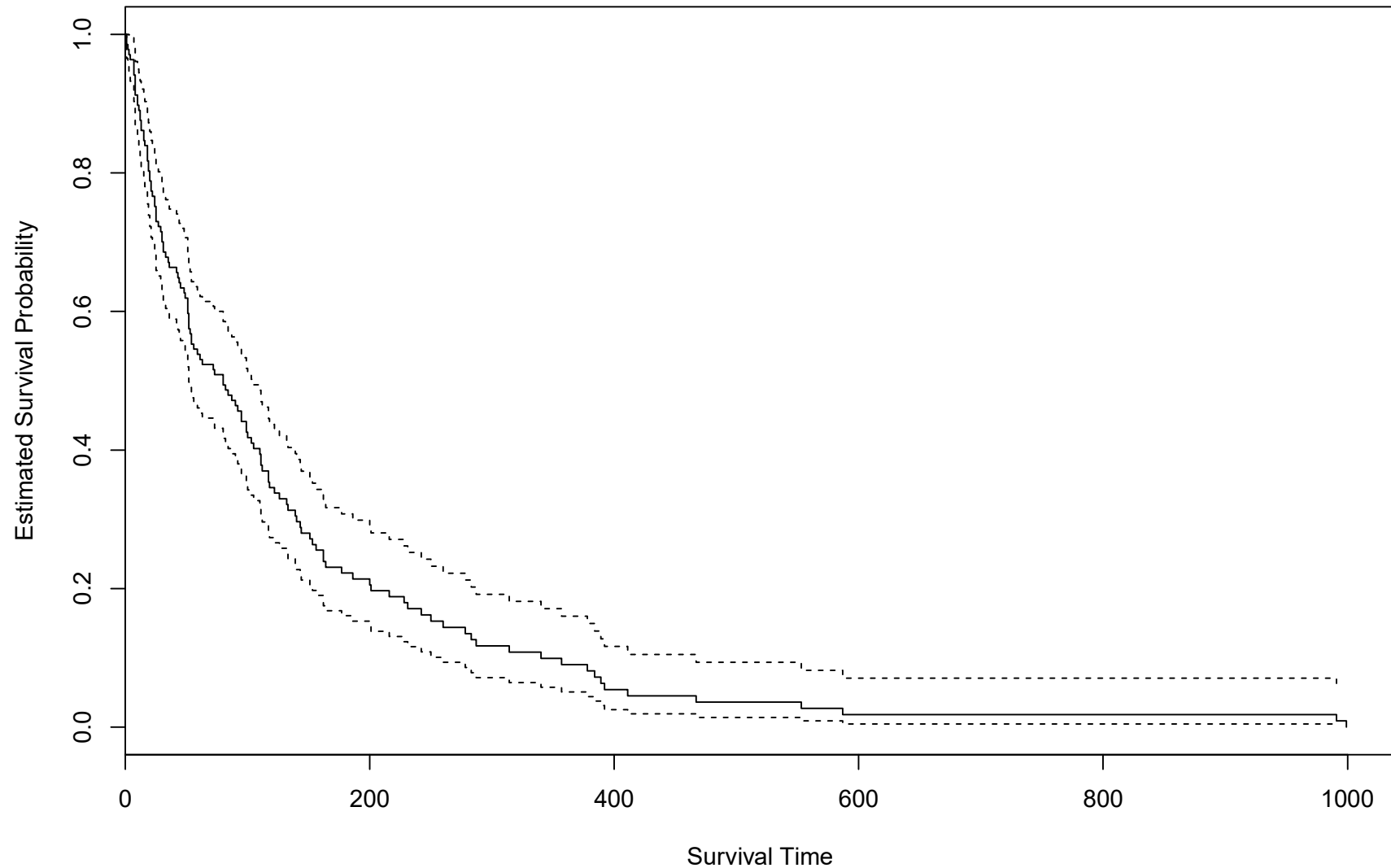
## veteran dataset

- ▶ trt: 1=standard 2=test
- ▶ celltype: 1=squamous, 2=smallcell, 3=adeno, 4=large
- ▶ time: survival time
- ▶ status: censoring status
- ▶ karno: Karnofsky performance score (100=good)
- ▶ diagtime: months from diagnosis to randomisation
- ▶ age: in years
- ▶ prior: prior therapy 0=no, 10=yes

See [R: Veterans' Administration Lung Cancer study](#) for more details.

## K-M estimate

We only consider time and status. Plot the Kaplan–Meier estimate of the survivor function.



## Review: K-M estimate

Code:

```
veteran.km = survfit(Surv(time,status)~1, data=veteran)
plot(veteran.km,xlab="Survival Time",
      ylab="Estimated Survival Probability" )
```

# Review: Cox proportional hazards model

Semiparametric model for hazard function:

$$h(t, X) = h_0(t) e^{\sum_{i=1}^p \beta_i X_i}.$$

- ▶  $h_0(t)$  is called *the baseline hazard function*.
- ▶ Proportional hazards assumption:  $h_0(t)$  only relies on  $t$ .
- ▶ Time-independence.

## Review: `coxph()` function

Description: Fits a Cox proportional hazards regression model. (Run `help('coxph')` for more details.)

```
cox = coxph(Surv(time,status)~trt,data=veteran)
```

*#Use `cox\$loglik` to get log likelihood ratio*

## Review: Construct CI for parameters

```
# .95 confident interval for `exp(coef)` (harzard ratio)
summary(cox)
```

```
## Call:
## coxph(formula = Surv(time, status) ~ trt, data = veteran
##
##      n= 137, number of events= 128
##
##              coef exp(coef) se(coef)      z Pr(>|z|)
## trt 0.01774      1.01790  0.18066 0.098    0.922
##
##      exp(coef) exp(-coef) lower .95 upper .95
## trt      1.018      0.9824    0.7144      1.45
##
## Concordance= 0.525  (se = 0.026 )
## Rsquare= 0      (max possible= 0.999 )
## Likelihood ratio test= 0.01  on 1 df,   p=0.9
## Wald test          = 0.01  on 1 df,   n=0.9
```

# Log-Log Plots

Our Proportional Hazard Model:

$$h(t) = h_0(t)e^{\beta x}.$$

Reminder (Textbook pg. 15):

$$S(t) = \exp \left[ - \int_0^t h(u) du \right]$$

So we have:

$$\log S(t) = - \int_0^t h_0(t)e^{\beta x} dt = -e^{\beta x} \int_0^t h_0(t) dt.$$



# Log-Log Plots

Log again:

$$\log(-\log(S(t))) = \beta x + \log \int_0^t h_0(t) dt.$$

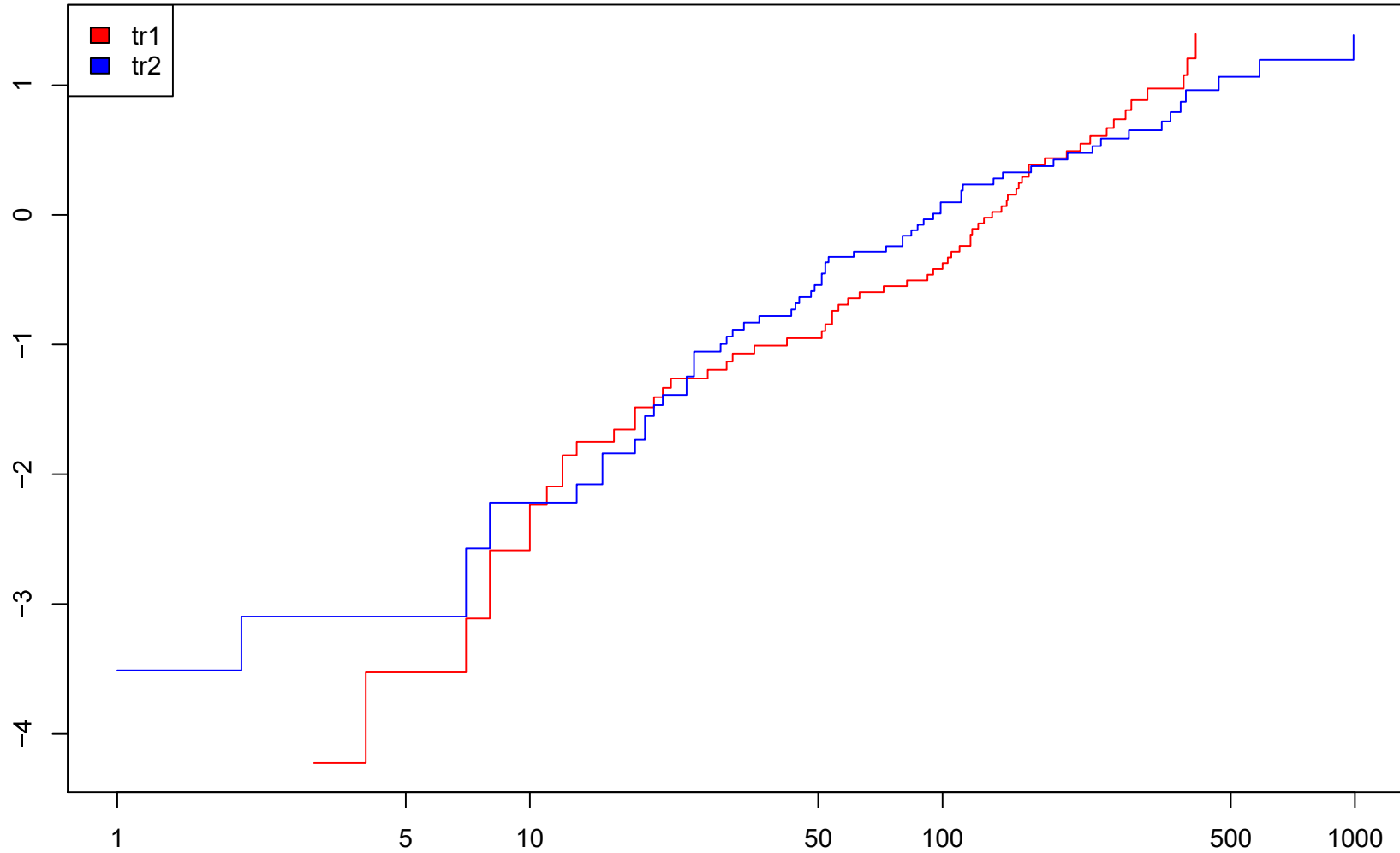
Comment: it should be linear in  $x$ .

# Log-Log Plots

Let fun='cloglog'. Code:

```
veteran.km = survfit(Surv(time,status)~trt, data=veteran)
plot(veteran.km, fun='cloglog', col=c('red','blue'))
legend('topleft',c("tr1","tr2"),fill = c("red","blue"))
```

# Log-Log Plots



## cox.zph() function

Description: Test the proportional hazards assumption for a Cox regression model fit (coxph).

(ref. cox.zph in R Documentation)

```
cox.zph(cox)
```

```
##           rho chisq          p
## trt -0.16    3.3 0.0691
```

## cox.zph() function

When  $p$  is small, it means there are time dependent coefficients.

The scaled Schoenfeld residuals are used in the cox.zph function.  
(ref: `residuals.coxph` in R documentation)

# Schoenfeld Residuals

