

# Practical biostatistics

Department of Clinical Epidemiology,  
Biostatistics and Bioinformatics

AMC

Cox Survival Analyse

# Day 8/9 Survival analysis

## ASSOCIATIONS

### CROSSECTIONAL

### LONGITUDINAL

#### BIVARIATE

#### MULTIVARIATE

Pearson's Rho

linear regression

Repeated measures:

GLM / mixed

Spearman's Rho

(non-linear regression)

Odds-ratio

logistic regression

(logistic reg. / discriminant)

survival analysis:

Kaplan-Meier / proportional hazards

# Cox-regression: between dis- and encouraging

## Altman

- *This section is more complex than the others in the book. (p. 387)*
- *Expert statistical advice should be sought for carrying out Cox regression on survival data. (p. 393)*

## Harris & Albert

- *The Cox model is basically very simple. (p. 93)*

# What is survival analysis ?

- A serie of statistical procedures to analyse a specific type of data:
  1. Outcome: time till event
  2. Study design:  
start follow-up      TIME      event  

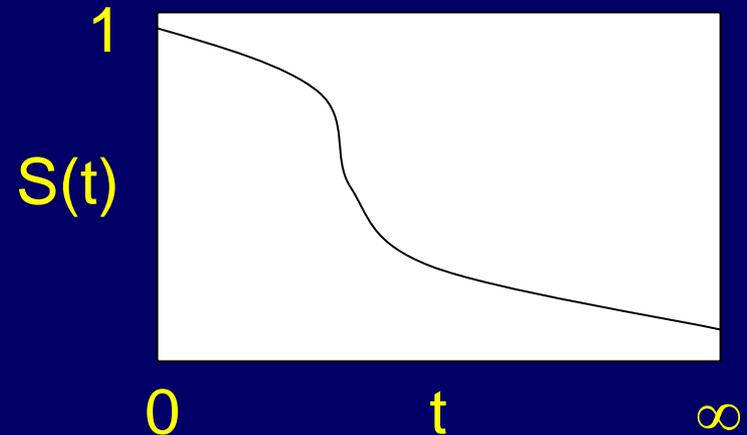
  3. Event: deceased, sick, relapse, recovery, etc. (assumption: event occurs just once and is unique)
  4. Time: years, months, days, weeks, seconds, ....

# Time until event

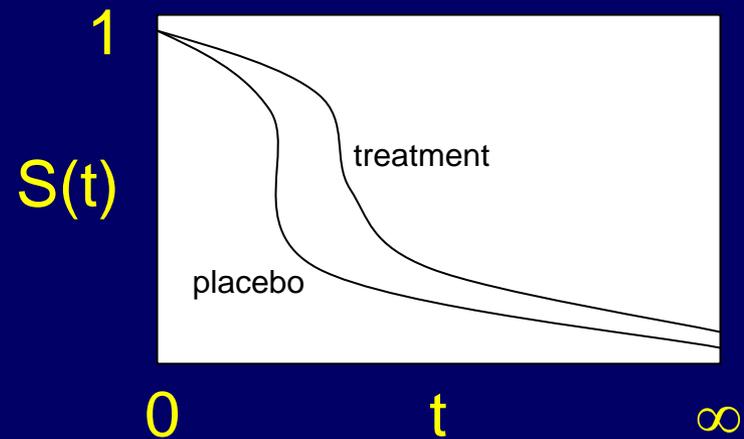
Start	Event	"Survival"
<i>Anti-hypertensive drug</i>	Myocard infarct	<i>Disease free period</i>
<i>Antibiotic</i>	Recovery	<i>Duration of the infection</i>
<i>HIV-infection</i>	Deceased	<i>Survival time</i>
<i>Statine</i>	Dementia	<i>Disease free period</i>

# Aim of survival analysis

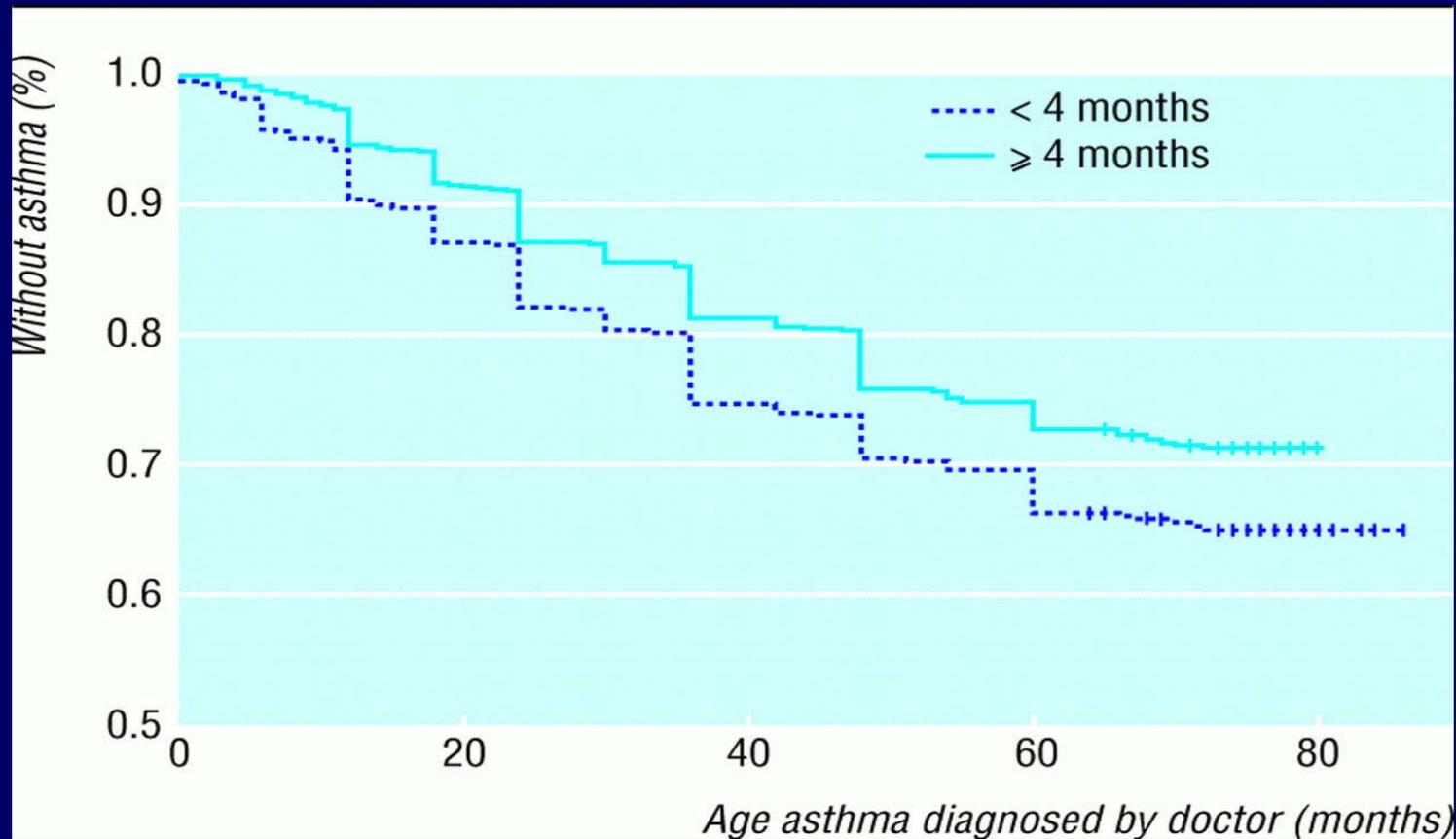
Estimation and interpretation of survival curves



Comparison of survival curves



Kaplan Meier survival functions for age at diagnosis of asthma stratified by duration of exclusive breast feeding  
(log rank statistic 10.70, df=1, P=0.001).

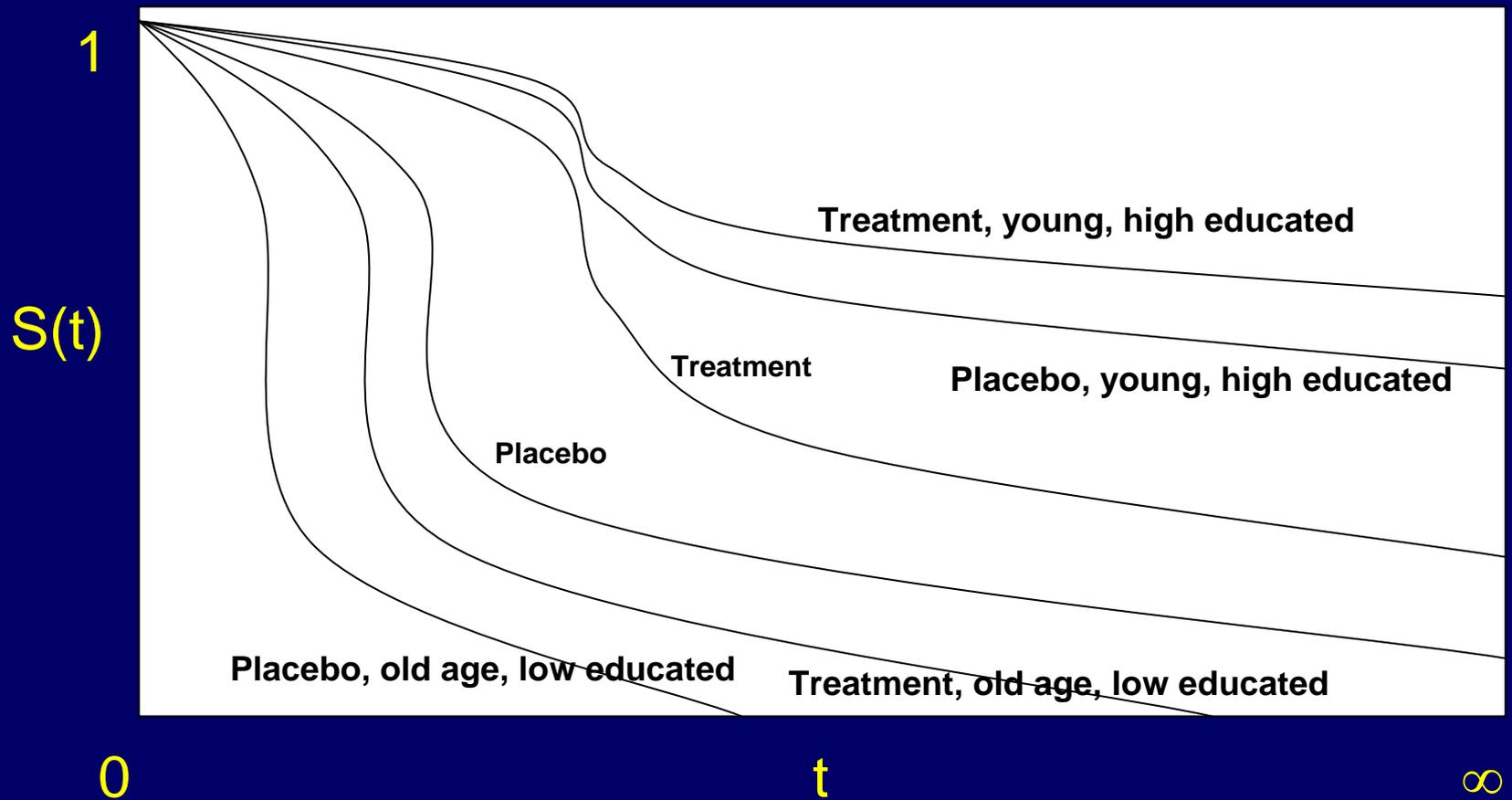


Vertical bars denote censoring events  
Oddy, Holt, Sly, et al. BMJ 1999

# Aim Cox regression analysis

To study the independent effects of a number of explanatory variables on survival

# Several influences



# Qualitative or quantitative

- Log-rank test:
  - Is there a difference, if so in what direction?
- Cox-regression:
  - How large is the difference and what is the influence of other predictive factors?

# Regression analysis

---

Kind of regression	Dependent variable $y$	Outcome
Linear	continuous	regression coefficient $\beta$
Logistic	binary	odds ratio $e^\beta$
Cox	time until event (censoring)	hazard ratio $e^\beta$

---

# Formulas

Linear regression:

$$y = a + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_k x_k$$

Logistic regression:

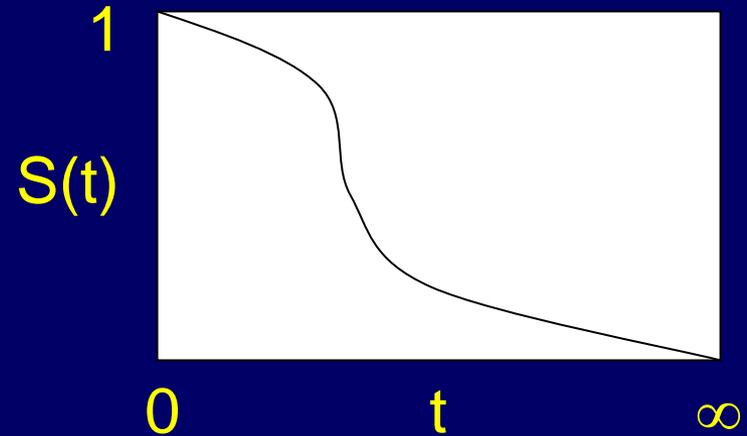
$$\ln(\text{odds}) = a + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_k x_k$$
$$\text{OR} = e^\beta$$

Cox regression:

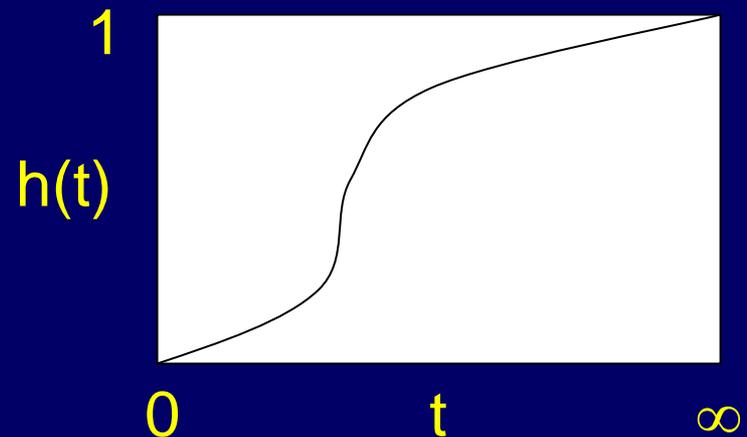
$$\ln(h(t)) = \ln(h_0(t)) + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_k x_k$$
$$\text{HR} = e^\beta$$

# Survival vs hazard

Cumulative survival



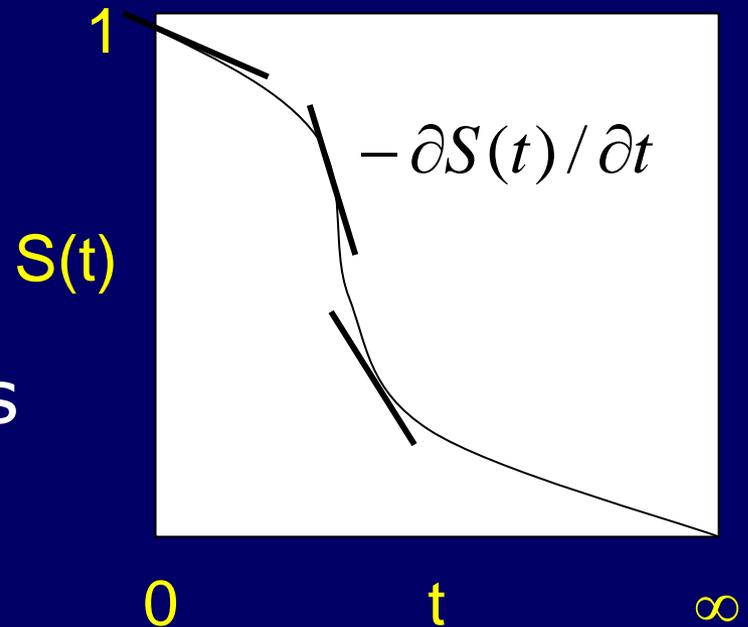
Cumulative hazard rate



# From $S(t)$ to $h(t)$ ; hazard rate

Hazard rate is the instant event rate in relation to the proportion survivors until time  $t$ , so:

$$h(t) = -\frac{\partial S(t)/\partial t}{S(t)} = -\frac{S'(t)}{S(t)}$$



# Cox regression model (log-linear)

patient  $i$

$$h_i(t) = h_0(t) * e^{\beta_1 x_{1i} + \beta_2 x_{2i} + \dots + \beta_p x_{pi}}$$

hazard function

basis hazard function

coefficients

predictors

# Elements of the Cox-model

$$h_0(t)$$

- Basis hazard function
- Dependent of time
- Can take any form (non-parametric)
- Valid for an average patient for all predictors

$$e^{\beta_1 x_{1i} + \beta_2 x_{2i} + \dots + \beta_p x_{pi}}$$

- Coefficients and predictors
- Independent of time, so: constant
- regression coefficients have to be estimated (parametric) and tested for significance
- if  $\beta=0$ , no effect

# Hazard ratio (HR): constant over time

IF:

$$h_i(t) = h_0(t) * e^{\beta_1 x_{1i} + \beta_2 x_{2i} + \dots + \beta_p x_{pi}}$$

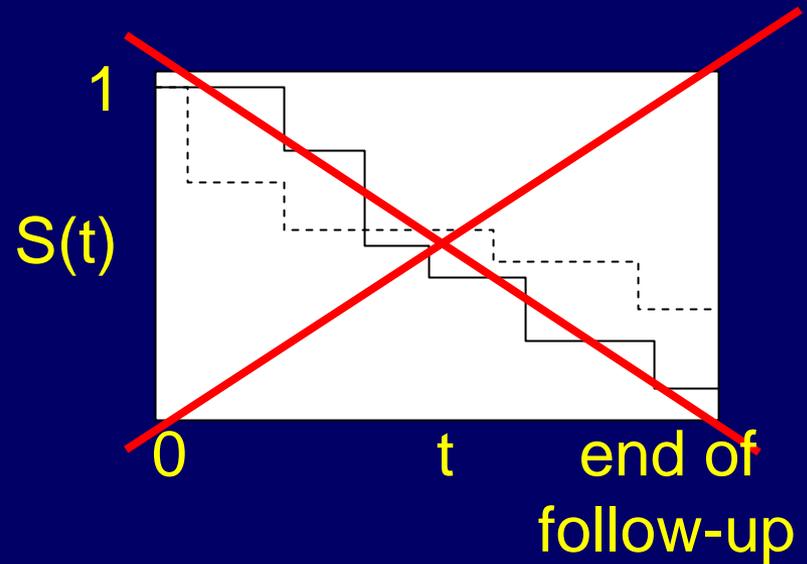
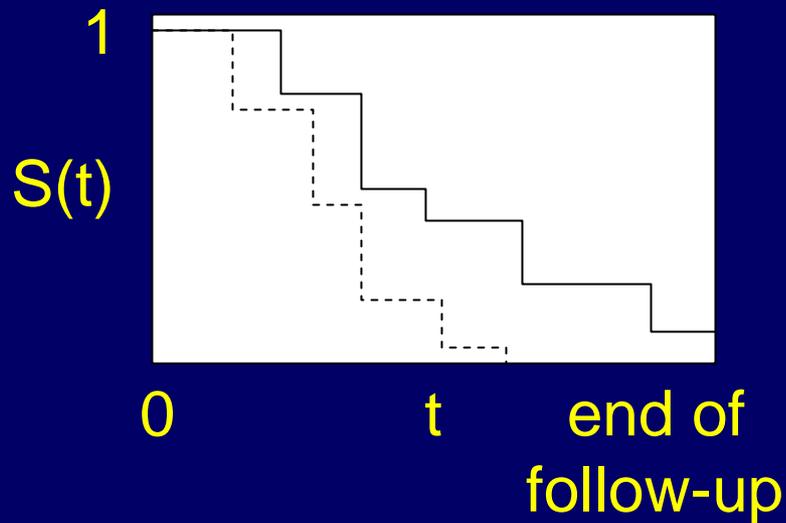
Then:

$$h_i(t)/h_0(t) = e^{\beta_1 x_{1i} + \beta_2 x_{2i} + \dots + \beta_p x_{pi}}$$

= constant

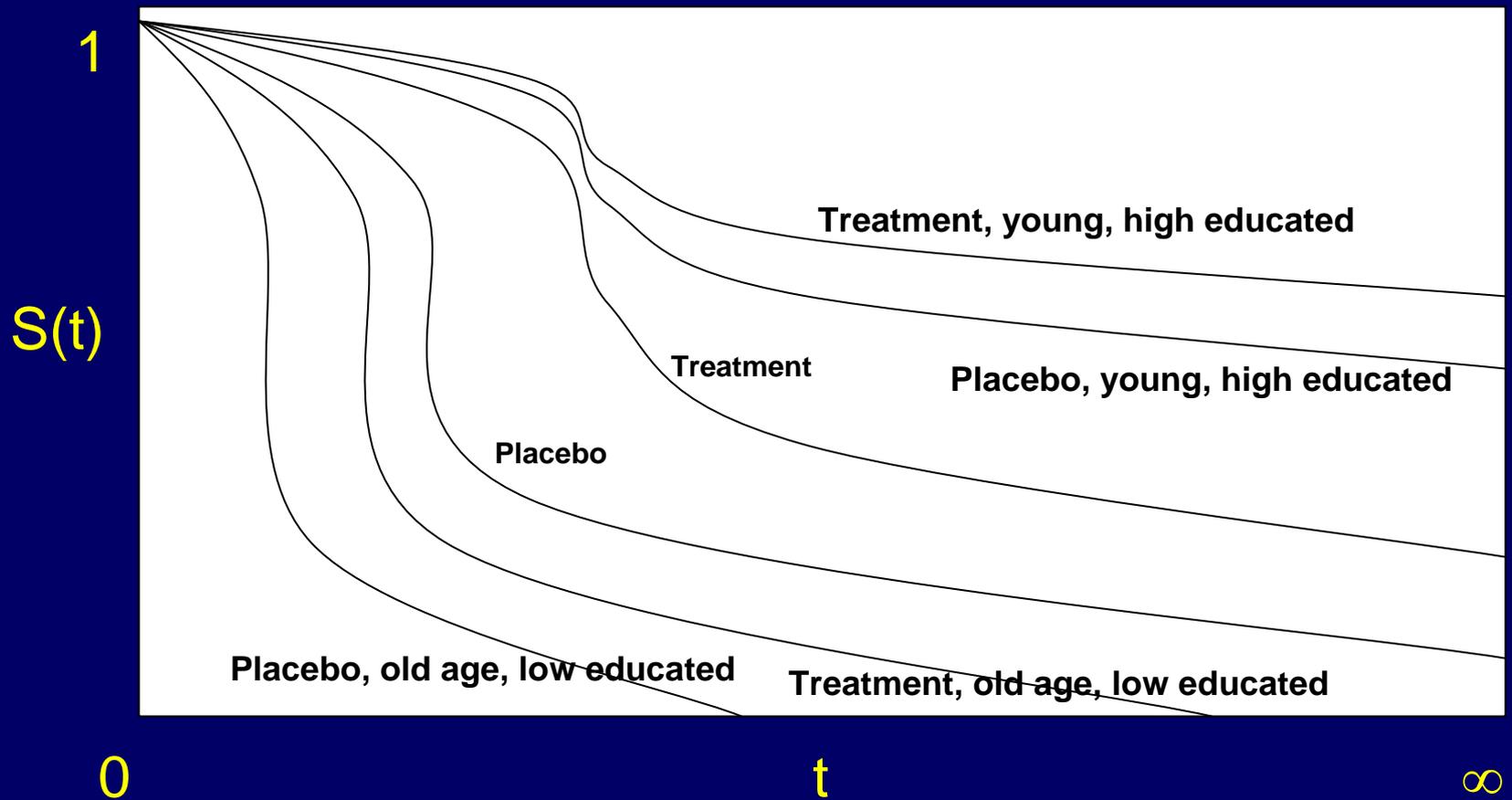
Assumption: proportional hazards (PH)

# PH assumption



Assumption: proportional hazards (PH), so:  
survival curves are not allowed to cross each other

# Several influences



# Example

1 
$$h_i(t) = h_0(t) * e^{\beta_1 \text{treatment}_i + \beta_2 \text{age}_i + \beta_3 \text{education}_i}$$

2 
$$h_i(t) = h_0(t) * e^{\beta_1 \text{treatment}_i + \beta_2 \text{age}_i}$$

3 
$$h_i(t) = h_0(t) * e^{\beta_1 \text{treatment}_i}$$

# Best model

- Comparison of the models with likelihood-ratio test:

$$-2 \log \frac{L_{\text{model1}}}{L_{\text{model2}}} = -2 (\log L_{\text{model1}} - \log L_{\text{model2}})$$

- This test behaves like a  $\chi^2$  with  $df=q$ ,
- $q$  is the number of additional covariates

# Best model

Comparison of the models with  
likelihood-ratio test:

Closer to zero is better

File Edit View Data Transform **Analyze** Graphs Utilities Window Help

1 : pid 1

	pid	weight			
1	1	62,0			
2	2	52,0			
3	3	74,0			
4	4	75,0			
5	5	81,0			
6	6	60,0			
7	7	70,0			
8	8	76,0			
9	9	60,0			
10	10	72,0			
11	11	71,0			
12	12	65,00	168	0	
13	13	58,50	168	0	
14	14	90,00	168	1	
15	15	71,00	173	1	
16	16	70,00	160	0	
17	17	64,00	173	1	

Reports  
 Descriptive Statistics  
 Tables  
 Compare Means  
 General Linear Model  
 Mixed Models  
 Correlate  
 Regression  
 Loglinear  
 Classify  
 Data Reduction  
 Scale  
 Nonparametric Tests  
 Time Series  
**Survival**  
 Multiple Response  
 Missing Value Analysis...

dbirth site donset

dbirth	site	donset
11-MAR-1921	Arm	15-DEC-85
01-DEC-1935	Leg	15-SEP-87
28-JUN-1922	Bulb	15-JUN-87
24-APR-1927	Arm	15-FEB-88
06-SEP-1916	Bulb	15-SEP-86
14-JUL-1915	Arm	15-DEC-86
29-NOV-1948	Arm	15-APR-88
16-AUG-1927	Leg	15-JAN-87
20-JUN-1921	Bulb	15-JUN-86
		JUN-86
		SEP-86
		JUL-88
10-JUL-1925	Leg	15-DEC-87
04-JUL-1926	Arm	15-JAN-88
21-SEP-1932	Arm	15-DEC-87
07-OCT-1928	Leg	15-FEB-88
17-NOV-1928	Leg	15-JUN-88

Life Tables...  
 Kaplan-Meier...  
**Cox Regression...**  
 Cox w/ Time-Dep Cov...



### Cox Regression

**Time:**

**Status:**

Block 1 of 1

**Covariates:**

**Method:**

**Strata:**

- # Patient [pid]
- # Weight at visit 0 [we]
- # Length [length]
- # Male [male]
- # Date of birth [dbirth]
- # Site of onset [site]
- # Date of onset [dons]
- # Date of diagnosis [d
- # Allocation [code]
- # Bulbar function at vi
- # Barthel ind. at visit C
- # Barthel ind. at visit 1
- # Rankin at visit 0 [rar
- # Total MRC score at
- # Age at onset (yr) [ag
- # Age at randomisatio
- # Died (12 mon) [deat
- # D.C. at visit 0 [dcs0]

1:									et	ddiagn
									C-85	15-JAN-88
									P-87	15-JUN-88
									N-87	15-AUG-88
									B-88	15-AUG-88
									P-86	15-AUG-88
									C-86	15-MAY-88
									R-88	15-NOV-88
									N-87	15-OCT-88
									N-86	15-APR-88
									N-86	15-MAY-87
									P-86	15-NOV-87
									L-88	15-DEC-88
									C-87	15-FEB-89
									N-88	15-JUL-88
									C-87	15-DEC-88
									B-88	15-JAN-89
17	17	64,00	172	1	17-NOV-1938	Leg	15-JUN-88	15-SEP-88		
18	18	63,00	168	0	28-APR-1941	Leg	15-JUL-88	15-FEB-89		
19	19	89,00	158	0	09-SEP-1925	Bulb	15-SEP-88	15-FEB-89		
20	20	75,00	183	1	21-MAR-1925	Leg	15-SEP-88	15-MAR-89		

## Block 0: Beginning Block

### Omnibus Tests of Model Coefficients

-2 Log Likelihood
720,496

## Block 1: Method = Enter

### Omnibus Tests of Model Coefficients<sup>a,b</sup>

-2 Log Likelihood	Overall (score)			Change From Previous Step			Change From Previous Block		
	Chi-square	df	Sig.	Chi-square	df	Sig.	Chi-square	df	Sig.
710,499	9,324	1	,002	9,997	1	,002	9,997	1	,002

a. Beginning Block Number 0, initial Log Likelihood function: -2 Log likelihood: 720,496

b. Beginning Block Number 1. Method = Enter

### Variables in the Equation

	B	SE	Wald	df	Sig.	Exp(B)	95,0% CI for Exp(B)	
							Lower	Upper
ageonset	,036	,012	9,193	1	,002	1,036	1,013	1,061

# Interpretation HR

- Suppose, model 3 is the best description of 'reality', and  $\beta_1 = -0.7$ . What is the hazard ratio (relative risk) for a patient treated with new treatment (treatment=1) and for a patient treated with placebo (treatment=0)?

$$\begin{aligned} \frac{h_1(t)}{h_2(t)} &= \frac{h_0(t) * e^{-0.7 * \text{treatment}_1}}{h_0(t) * e^{-0.7 * \text{treatment}_2}} \\ &= e^{-0.7 * (\text{treatment}_1 - \text{treatment}_2)} \\ &= e^{-0.7 * (1 - 0)} = 0.496 \end{aligned}$$

# Check PH assumption

- survival curves: no crossing !
- log - log survival curves: parallel !

## Violation of PH

- stratified Cox regression
- introduction time-dependent variables

# In summary

- Use Cox-regression to study the independent effects of explanatory variables on survival
- Results: Hazard ratio's (relative risks)
- Choose best model using likelihood ratio test
- Check PH-assumption