# Biostatistics

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#### New Material from Last Week

- We discussed "sequential" or "group sequential" experiments
  - You do one or more interim analyses to see if you can stop the experiment early
  - If "significant" stop and reject the null, if not continue
- Example: Your total sample size is 10 per group, you have two groups and you do one interim analysis when you reach 5 per group
  - If you use p<0.05 both at interim analysis and at the end your Type I error probability with be 0.075.

## How to do it Right?

- There are many (inifinetely many) pairs of p-values thresholds (one for interim one for final) that will make it work
  - If you use p<0.03 both at the interim analysis and at the final analysis, then your Type I error probability is 0.05.
  - If you use p<0.009 at the interim analysis and p<0.0467 at the final analysis, then your Type I error probability is 0.05.

### Another Example

- Optimal Cutoff
- A continuous predictor, either a continuous, binary or survival outcome
- Goal is to find the optimal cutoff to dichotomize the predictor and then a generate a p-value for the resulting two sample comparison
- If you use p<0.05 your Type I error is probability 0.40!!!
- You need a tailored method for this (called maximal chi-square method)

## Analysis of Binary Outcomes

- We have two groups and a binary outcome
- Ex: Treatment and response
- N<sub>1</sub> patients in treatment A and N<sub>2</sub> in treatment B
- R<sub>1</sub> responders (of N<sub>1</sub>) in A and R<sub>2</sub> (of N<sub>2</sub>) in B
- Response rates of  $R_1/N_1$  and  $R_2/N_2$

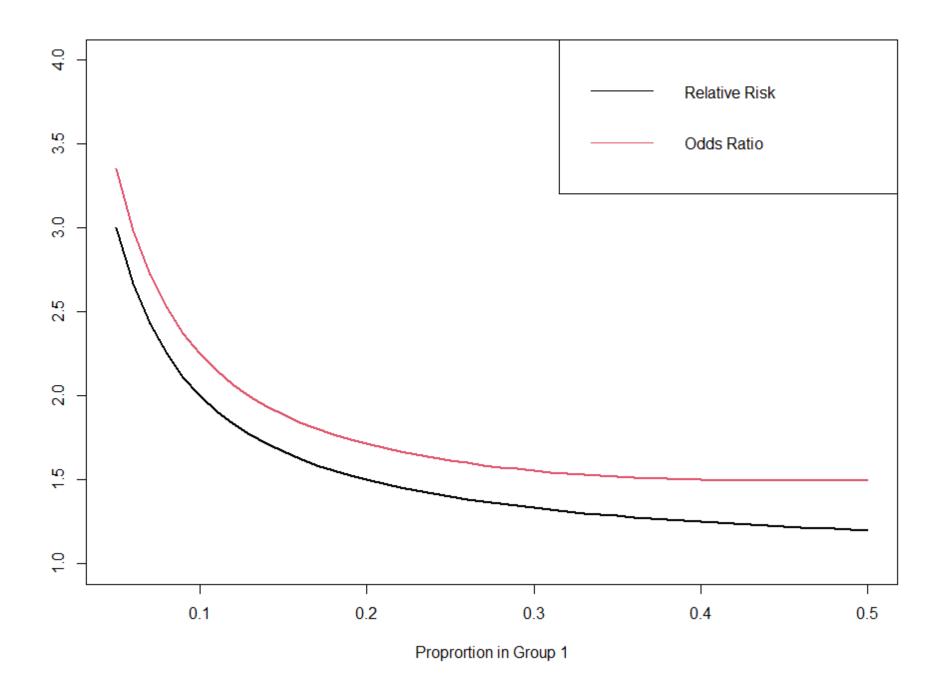
#### 2x2 Table

	Response	No Response	TOTAL
Treatment A	$R_1$	N <sub>1</sub> - R <sub>1</sub>	$N_1$
Treatment B	$R_2$	$N_2 - R_2$	$N_2$
TOTAL	$R_1 + R_2$	$N_1 - R_1 + N_2 - R_2$	$N_1 + N_2$

- Think of a 2x2 table anytime you have a binary outcome and 2 groups
- Think of a KxP table any time you have an outcome with K categories and P groups
- All the information in the data we need is here
- Very useful and flexible display

#### Difference, Relative Risk, Odds Ratio

- Proportions: R1/N1 = p1 and R2/N2 = p2
- Three metrics for summarizing the difference
  - Difference: p1 p2
  - Relative Risk: p1/p2
  - Odds Ratio: [p1/(1-p1)] / [p2/(1-p2)]
- Important note: Odds Ratio is often interpreted as a relative risk (e.g., 2-fold increase in risk) but it is not



### Hypothesis Testing in a 2x2 Table

	Response	No Response	TOTAL
Treatment A	$R_1$	N <sub>1</sub> - R <sub>1</sub>	$N_1$
Treatment B	$R_2$	$N_2 - R_2$	$N_2$
TOTAL	$R_1 + R_2$	$N_1 - R_1 + N_2 - R_2$	$N_1 + N_2$

- Null hypotheses: Response rates are the same
- Alternative: They are not the same
  - Is this one-sided or two-sided?
- How to test this null?
  - We need a test statistic

## Chi-Square Test

- For historical reasons, the derivation of this test was done differently and involved the chi-square distribution instead of the normal
- This idea more easily generalizes to bigger tables
- Chi-square test is always two-sided (memorize this) and does not lend itself to a confidence interval easily
- But used all the time in practice, partly because it applies to difference, relative risk and odds ratio equally.

#### Fisher's exact test

	Response	No Response	TOTAL
Treatment A	$R_1$	N <sub>1</sub> - R <sub>1</sub>	$N_1$
Treatment B	$R_2$	$N_2 - R_2$	$N_2$
TOTAL	$R_1 + R_2$	$N_1 - R_1 + N_2 - R_2$	$N_1 + N_2$

- Under the null hypothesis of equal response rates and N<sub>1</sub> patients in treatment A and N<sub>2</sub> in B, how many do you expect to response in Treatment A?
- Involves something called a hypergeometric distribution
- Use it if available, definitely use it in small tables (even if one cell is small; eye of the beholder but <5 is commonly cited)</li>

# Summary of the 2x2 Table

- Three metrics: Difference, Relative Risk, Odds Ratio
- Two test statistics
  - Chi-Square test
  - Fisher's exact test

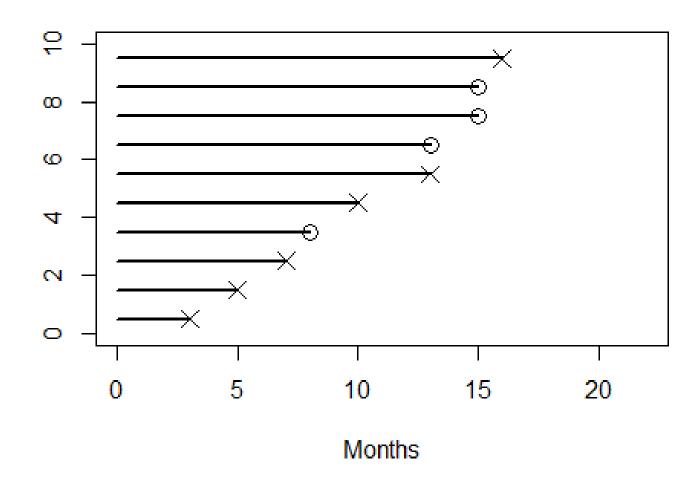
## Survival Analysis

- Most important cancer outcomes are time-to-event
  - Time to death (overall survival)
  - Time to cancer death (disease specific survival)
  - Time to progression (progression free survival)
- Time interval between a "baseline" and an event
- Continuous variable?
- What is the big deal?

#### Censoring

- You are VERY VERY unlikely to observe all patients have the event of interest
- Some people will be alive or free of progression when the data analysis time comes
- This is called censoring, a data point that is not (yet) fully observed
  - Unfortunate terminology
- Primary reason why survival analysis requires special treatment

Data: 3, 5, 7, 8+, 10, 13, 13+, 15+, 15+, 16



#### What Can We Do?

- Ignore censoring, analyze as continuous
  - Treats people under follow-up as if they died
  - Underestimates survival probabilities
- Ignore time, analyze binary
  - Someone who died at 10 years vs someone who is alive and under follow-up at 6 months
- Both wrong, should NEVER EVER be used

## Toy Example

- Data: 3, 5, 7, 8+, 10, 13, 13+, 15+, 15+, 16
- Do you remember the cumulative distribution function (CDF)?
- Plot P(survival time <= t) against t</li>
- We want the survival function: P(survival time > t) = 1 CDF
- Let's ignore censoring for a moment and act if everyone is dead
- P(survival time > t) = 1 until t = 3
- P(survival time > t) = 9/10 = 0.1 for t between 3 and 5
- P(survival time > t) = 8/10 = 0.2 for t between 5 and 7
- (# alive before or on t)/n

### Another way to calculate the survival function

- S(t) = 1, until t = 3
- S(t) = 9/10 = 0.9, between t=3 and t=5
- S(t) = (9/10)\*(8/9) = 8/10 = 0.8

Probability of making it to 3 months

Probability of making it to 5 months, given you made it to 3 months

9 people made it to 3 months, 8 of these 9 made it 5 months

New denominator: 9 people at risk of death at 5 months

9 People Are "AT RISK" at 3 months

• Prob of making it to 5 months = ?

- Prob of making it to 5 months = (8/10)
- Prob of making to 7 months given you have made it to 5 months = ?

- Prob of making it to 5 months = (8/10)
- Prob of making to 7 months given you have made it to 5 months = (7/8)
- Prob of making to 7 months = (8/10)\*(7/8) = (7/10) = 0.7

• Prob of making it to 7 months = ?

- Prob of making it to 7 months = (7/10)
- Prob of making to 8 months given you have made it to 7 months = ?

- Prob of making it to 7 months = (7/10)
- Prob of making to 8 months given you have made it to 7 months = (7/7)
- Prob of making to 7 months = (7/10)\*(7/7) = (7/10) = 0.7

- Prob of making it to 8 months = (7/10)
- Prob of making to 10 months given you have made it to 8 months = ?

- Prob of making it to 8 months = (7/10)
- Prob of making to 10 months given you have made it to 8 months = ?
- How many people are at risk past 8 months?

- Prob of making it to 8 months = (7/10)
- Prob of making to 10 months given you have made it to 8 months = (5/6)
- Prob of making to 7 months = (7/10)\*(5/6) = 0.583

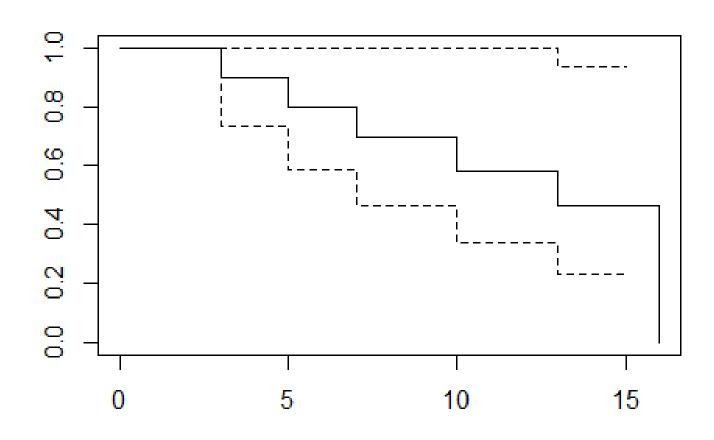
- Prob of making it to 10 months = 0.583
- Prob of making to 13 months given you have made it to 10 months =

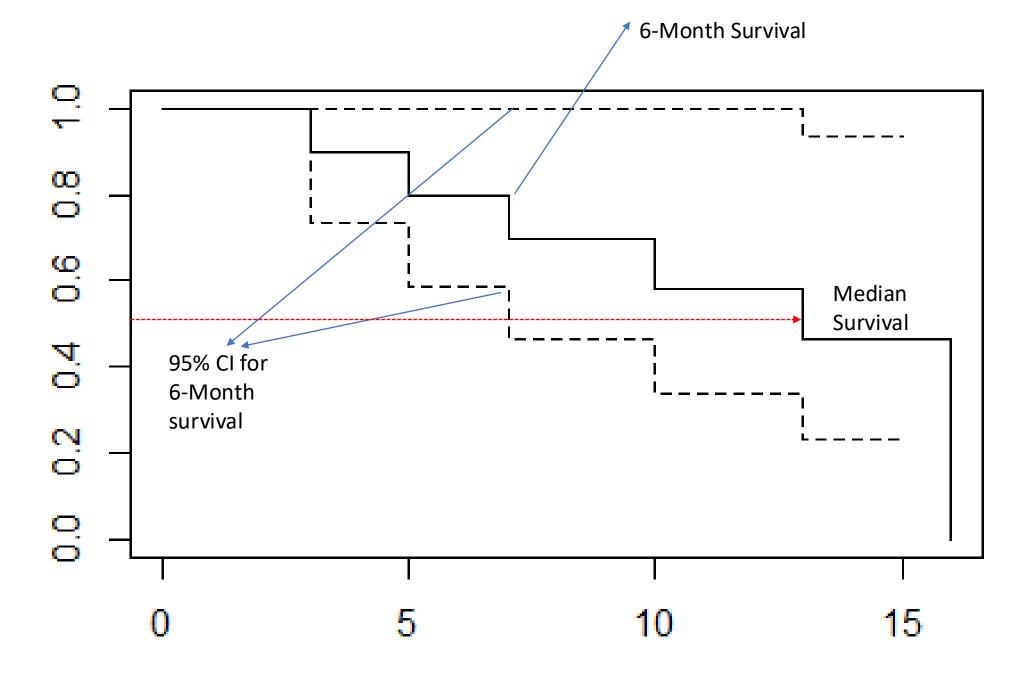
- Prob of making it to 10 months = 0.583
- Prob of making to 13 months given you have made it to 10 months = (4/5)
- Prob of making to 13 months = 0.583\*(4/5) = 0.467

- Prob of making it to 13 months = 0.467
- Prob of making to 15 months given you have made it to 13 months = (3/3)
- Prob of making to 15 months = 0.467\*(3/3) = 0.467

- Prob of making it to 15 months = 0.467
- Prob of making to 16 months given you have made it to 16 months = (0/1)
- Prob of making to 16 months = 0.467\*0 = 0

# Kaplan-Meier Curve!!!





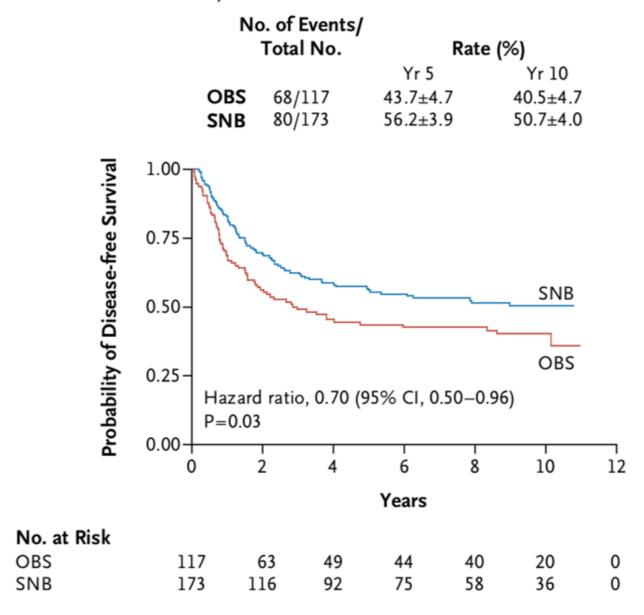
#### Characteristics of KM Curves

- Full information about survival
  - All probabilities
  - All quantiles, quartiles etc
- Jumps down at event times
- Stays the same at censoring times
  - This is why censoring times are indicated by tick marks
- Step sizes get larger and larger
  - Because the denominator gets smaller and smaller

### Key Concept

- Risk set, or the number at risk changes at each time point
- This is true even when there is no censoring; those who die move out of the risk set
- But when censoring is present, those who are censored also move out of the risk set at the time of censoring
- The idea of risk set underlies all survival analysis (Cox regression, competing risks, truncation etc)

#### D Disease-free Survival, Thick Melanomas



# Log-Rank Test

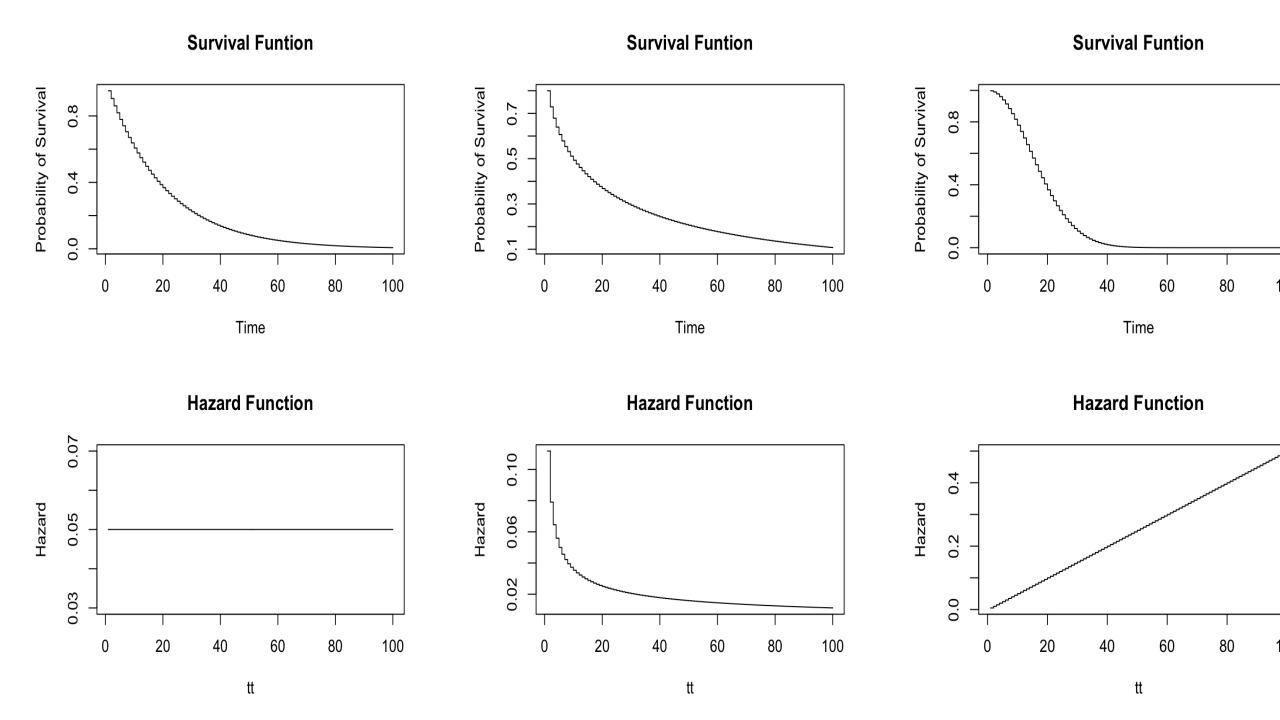
- Standard method of comparing survival curves
- At each time point one of the curves (or both) jumps, calculate the expected number of events at that time point if there is no difference between the curves
  - Why do we do this calculation assuming there is no difference?
- Compare the expected number with the observed (similar to the chisquare test)
- Add up the difference between observed and expected over all time points

#### Hazard Function

- Remember the survival curve, which represents one minus the cdf of the survival times?
- Call it S(t)
- Hazard function, h(t), is the derivative of the logarithm of S(t)
- $h(t) = (d/dt) \log(S(t))$

### Hazard Function: Interpretation

- Probability of dying between t and t+d, given one has survived up to t, divided by d, where d is a very, very small time interval
- Hazard is NOT probability
- It is probability scaled by a small length of time
- Numerically, not useful at all by itself
- But the shape of the hazard function is quite informative

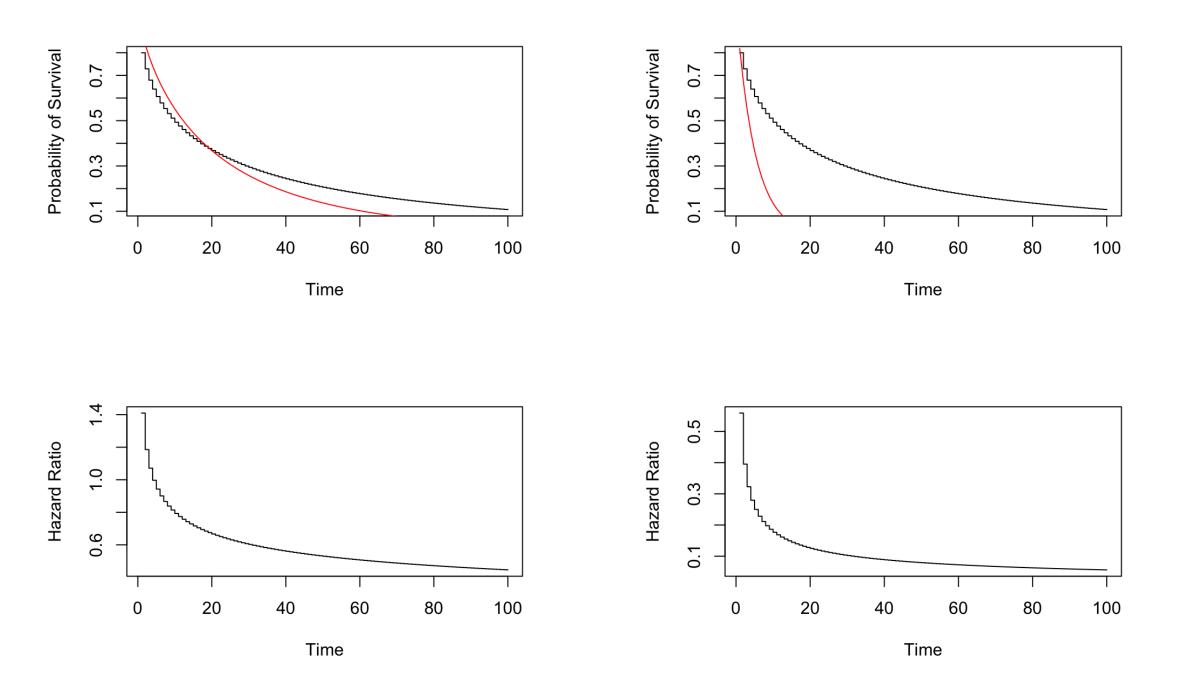


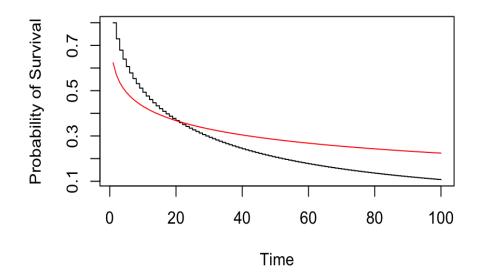
# Three Examples

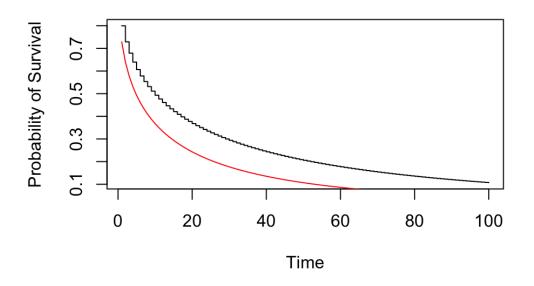
- Increasing hazard
  - Probability of death in population (over a long period of time)
- Decreasing hazard
  - Probability of cancer death or recurrence
- Constant hazard
  - 5

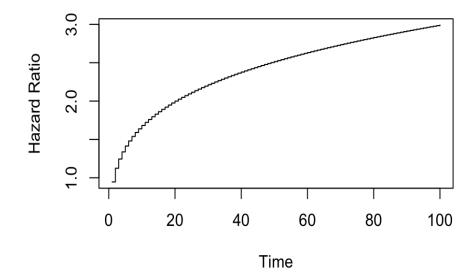
#### Hazard Ratio

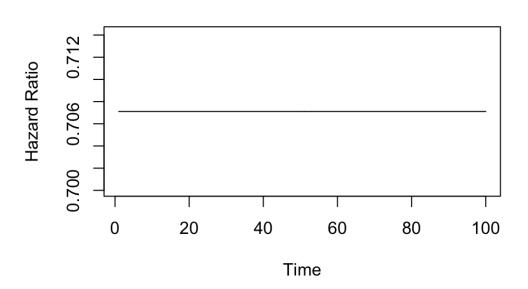
 Hazard function itself is not used very much but ratio of two hazard functions is commonly used to "compare" survival functions











#### Hazard Ratio

- Hazard function itself is not used very much but ratio of two hazard functions is commonly used to "compare" survival functions
- Constant hazard ratio → Proportional hazards (PH)
- Crossing survival curves → Not PH
- Converse is not true, one can have PH without survival curves crossing
- Eyeballing the survival curves to figure out hazard ratios is futile

## Restricted Mean Survival Time (RMST)

- Fact: Area under the survival curve is the mean survival time
- Why not used more often (or at all)?
- Unless survival curve drops to 0, you cannot estimate the mean
- Idea: choose a time point on your survival curve that is both clinically relevant and also "well-estimated" (i.e. still a reasonable number at risk)
- Calculate the area under the curve up to that time point
- $\bullet \rightarrow RMST$

### RMST Difference

- If the area under one curve is the mean
- Then the area between the curves is mean difference
- The are between the curves up to a time point is RMST Difference
- An alternative to HR to summarize the relative position of the curves
- Does not make assumptions
- But requires a "subjective" choice of time point
  - Although less influenced by this choice than, say, reporting S(t) at a chosen time point

### RMST Difference is most useful

- When PH does not hold
- Caveats:
- How can you tell PH does not hold?
  - Very difficult (unless curves cross)
  - The statistical tests developed for this are not powerful
- Need to be careful if curves cross
  - You will need to keep track of which curve is on top where and assign "a sign" to the area

### Neratinib Plus Capecitabine Versus Lapatinib Plus Capecitabine in HER2-Positive Metastatic Breast Cancer Previously Treated With ≥ 2 HER2-Directed Regimens: Phase III NALA Trial

Cristina Saura, MD¹; Mafalda Oliveira, MD, PhD¹; Yin-Hsun Feng, MD, PhD²; Ming-Shen Dai, MD, PhD²; Shang-Wen Chen, MD²; Sara A. Hurvitz, MD³; Sung-Bae Kim, MD, PhD⁴; Beverly Moy, MD, PhD⁵; Suzette Delaloge, MD, MSc⁶; William Gradishar, MD⁷; Norikazu Masuda, MD, PhD®; Marketa Palacova, MD⁰; Maureen E. Trudeau, MD¹⁰; Johanna Mattson, MD, PhD¹¹; Yoon Sim Yap, MBBS¹²; Ming-Feng Hou, MD¹³; Michelino De Laurentiis, MD, PhD¹⁴; Yu-Min Yeh, MD¹⁵; Hong-Tai Chang, MD¹⁶; Thomas Yau, MBBS, MD¹⁷; Hans Wildiers, MD, PhD¹³; Barbara Haley, MD²⁰; Daniele Fagnani, MD²¹; Yen-Shen Lu, MD, PhD²²; John Crown, MBBCh, MD²³; Johnson Lin, MD²⁴; Masato Takahashi, MD, PhD²⁵; Toshimi Takano, MD²⁶; Miki Yamaguchi, MD, PhD²⁷; Takaaki Fujii, MD, PhD²³; Bin Yao, MS²⁰; Judith Bebchuk, ScD²⁰; Kiana Keyvanjah, PharmD²⁰; Richard Bryce, MBChB²⁰; and Adam Brufsky, MD, PhD³⁰; for the NALA Investigators

