LONDON SCHOOL of HYGIENE & TROPICAL MEDICINE

Model selection and explained variation of survival from cancer

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Background and aims

- Model selection for *estimation* of cancer survival
  - Akaike Information Criterion (AIC)
- Model selection for *prediction* of cancer survival
  - ➢ Ideas:
  - AIC-based measures of goodness of fit
  - Measures of explained variation

AIC-based measures of Goodness of Fit

- To help detect likely form of the predictors
- To investigate model-averaging

➢ AIC & AIC-derived measures: overall and by age group

➢ AIC-differences: $d_i = AIC_i - \min_{j=1:N}(AIC_j)$

➢ Model likelihood: $l_i = \exp(-d_i/2)$

➢ AIC weights: $w_i = l_i / \text{sum}_{j=1:N}(l_j)$

i – model in consideration

N – total number of models considered

A measure of explained variation: R_E

- R_E
  - Stands for "Ranks Explained"
  - Non-parametric
  - Model-free interpretation
  - Well-understood scale: [-1; +1]
  - Consistent with independent censoring mechanisms
- Stare J., et al. *A Measure of Explained Variation for Event History Data*, Biometrics, 2010

➢ To be adapted to the net survival context

R_E in the overall survival context

$$R_E = \frac{\sum_i (r_{i,null} - r_{i,model})}{\sum_i (r_{i,null} - r_{i,perfect})}$$

Summation over all observations that fail

i: time at which the i^{th} observation fails

$r_{i,null}$: rank of observation *i* under the null model

→ all observations in risk set have equal chances to fail at time t_i

$r_{i,perfect}$: rank of observation *i* under the perfect model

→ observation *i* is given rank 1

R_E in the net survival context

$$R_E = \frac{\sum_i (r_{i,LT} - r_{i,model})}{\sum_i (r_{i,LT} - r_{i,perfect})}$$

Summation over all observations that fail

i: time at which the i^{th} observation fails

$r_{i,LT}$: rank of observation *i* by the life tables

→ all observations in risk set have unequal chances to fail at time *i*

$r_{i,perfect}$: rank of observation *i* under the perfect model

→ observation *i* is given rank 1

Test of R_E in the net survival context

- Simulated datasets
  - 2000 colon cancer patients
  - Age at diagnosis 15-99 years (mean age 70)
  - Distribution of stage at diagnosis
    - 13% - stage I
    - 40% - stage II
    - 27% - stage III
    - 20% - stage IV
- Scenarios: varying effects of age and stage at diagnosis on cancer-survival

  Time-fixed *vs.* time-varying

  Linear *vs.* non-linear
- 100 datasets per scenario

Results: R_E in the net survival context

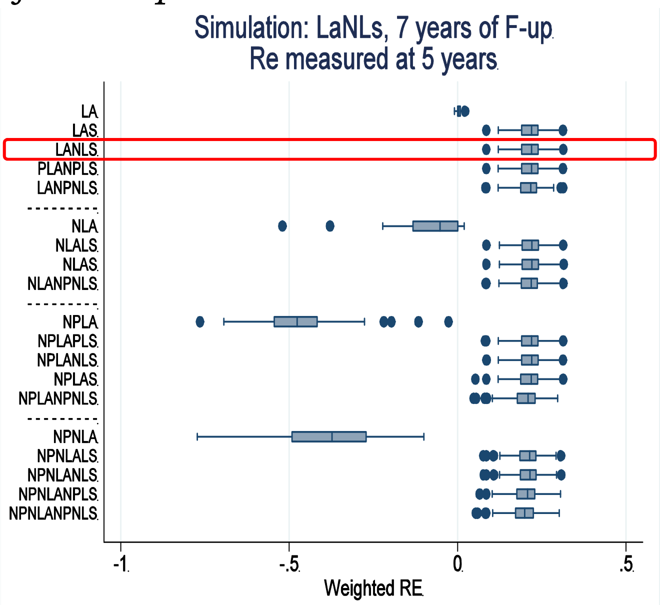
7 years of follow-up

Prop.
Linear age

Prop.
Non-linear age

Non-prop.
Linear age

Non-prop.
Non-linear age



Results: R_E in the net survival context

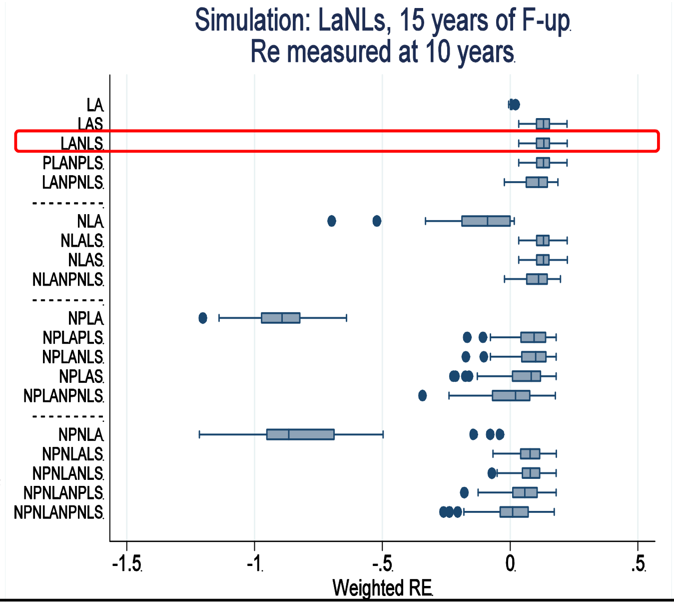
15 years of follow-up

Prop.
Linear age

Prop.
Non-linear age

Non-prop.
Linear age

Non-prop.
Non-linear age



Results: R_E in the net survival context

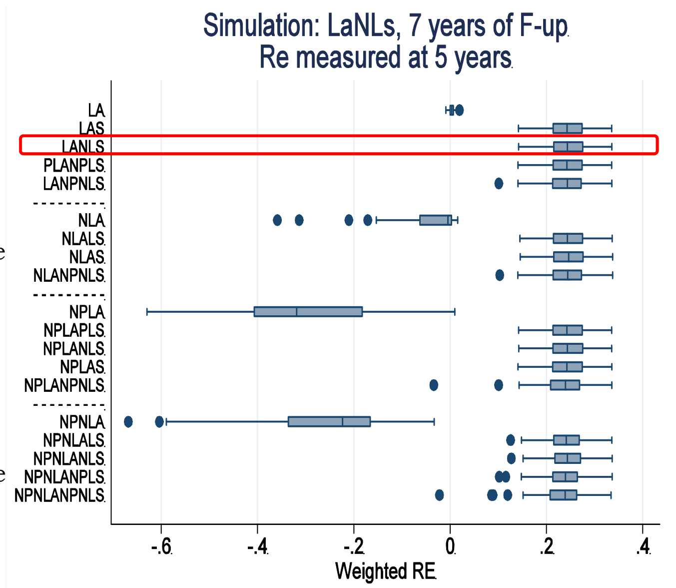
Censoring

Prop.
Linear age

Prop.
Non-linear age

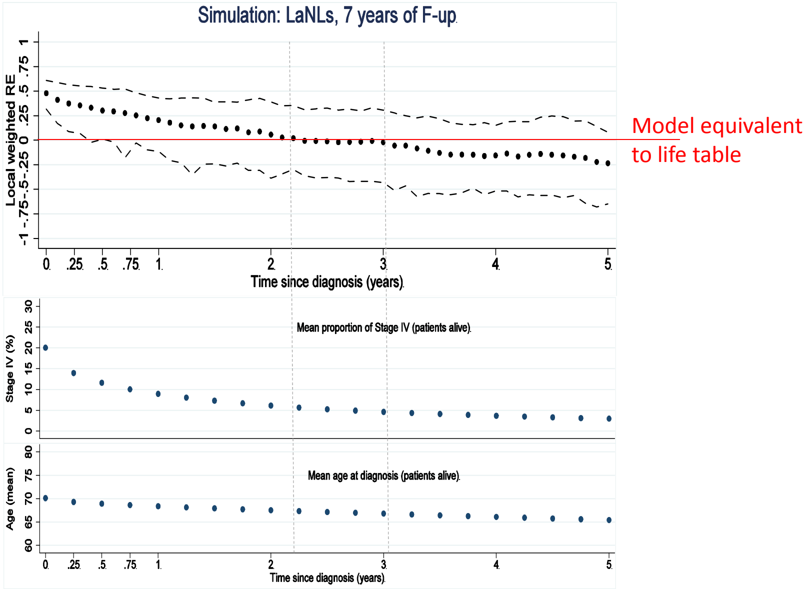
Non-prop.
Linear age

Non-prop.
Non-linear age



Results: R_E in the net survival context

Time-varying effect



Discussion

- R_E not sensitive to models which do not affect the rank order
- Informative null model
  - Pros: reflect the nature of net survival model
  - Cons:
    - values never high (survival issue)
    - values for R_E can go beyond -1
- Local R_E: tool for understanding time-varying impact of risk factors on cancer survival
- Additional potential predictors

➢Future
  - Model-averaging
  - Frailty model