

How to estimate beta-interferon treatment effectiveness in MS using some fancy modelling

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Observational
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Outline

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- ① Why modelling
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Why modelling > Objective

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- **Outcome:** Reaching a milestone in disability progression (time to sustained EDSS 6)
- **Treatment:** Use of β -interferons (3 kinds)
- **Objective:** Treatments have any long-term beneficial effect?

Randomized controlled trial or **observational** study?

Why modelling > Treatment Effect

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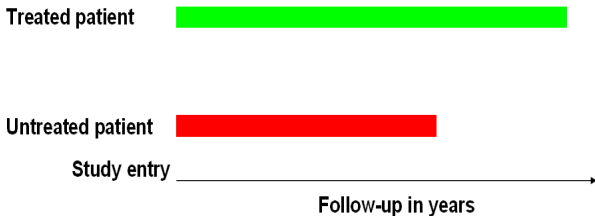
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Treatment Effect from ideal situation

Why modelling > Treatment Effect

Why modelling

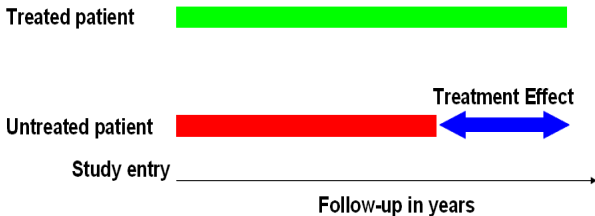
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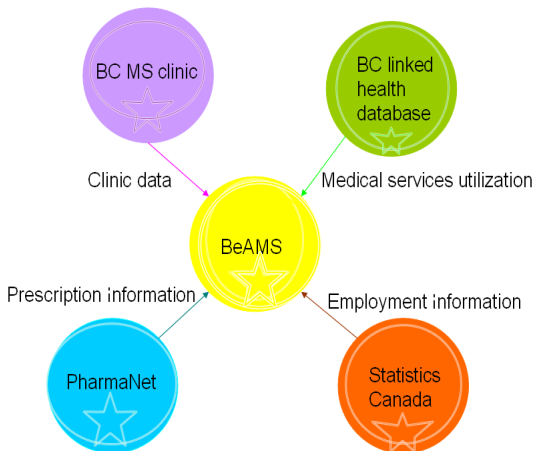
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Treatment Effect from ideal situation: KM / Cox PH model?

Why modelling > Less than ideal situation



Baseline covariates: Gender, Age, Disease duration

Time-varying covariates: Relapse, EDSS scores

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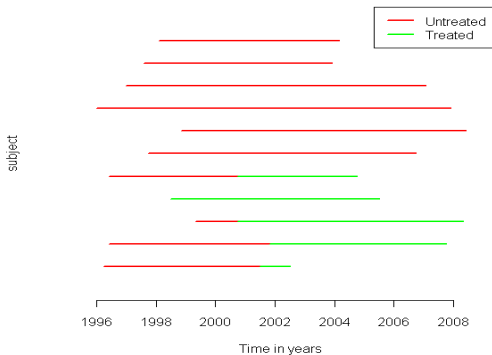
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Patients are selected with **similar eligibility criteria**.

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Time-dependent (treatment) Cox Model:

$$\lambda_{T_{\bar{a}}}(t|V) = \lambda_0 \times \exp(\beta_1 a(t) + \beta_2 V + \beta_3 L)$$

Hazard

Hazard
at baseline

Treatment
at time t

Baseline
covariates

more
covariates?

(1) Gender,
(2) Age,
(3) Disease
duration

(4) Relapse,
(5) EDSS score

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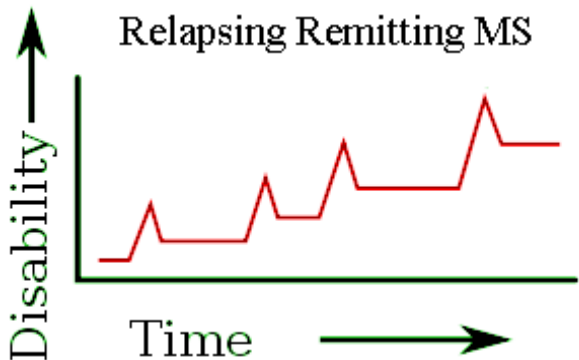
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Why modelling > Why time dependent covariate



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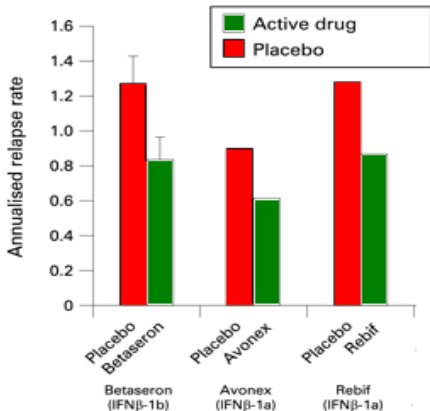
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[Coles, 2009]

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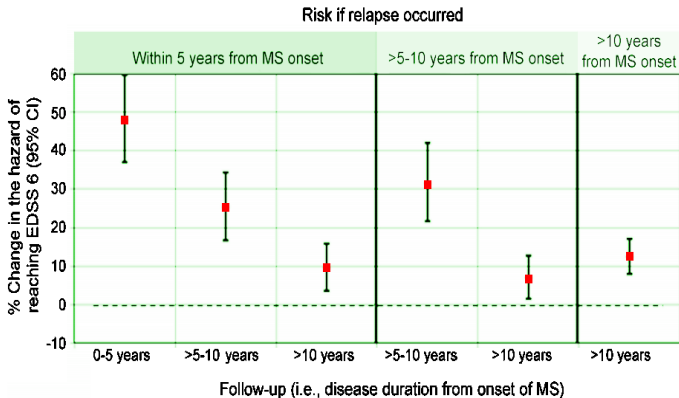
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Why modelling > Why time dependent covariate

Impact of a relapse on the hazard of reaching EDSS 6 at different time points



[Tremlett et al., 2009]

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Why modelling > Extended Cox-model?

Time-dependent Cox Proportional Hazards Model:

$$\lambda_{T_{\bar{a}}}(t|V) = \lambda_0 \times \exp(\beta_1 a(t) + \beta_2 V + \beta_3 L(t))$$

Hazard	Hazard at baseline	Treatment at time t	Baseline covariates	Time-dependent covariates
			(1) Gender, (2) Age, (3) Disease duration	(1) Relapse, (2) EDSS score

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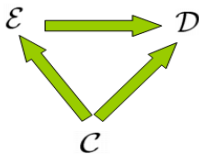
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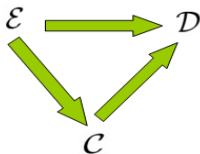
References

Why fancy modelling > Causal Graphs

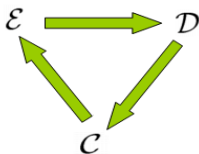
Common Cause



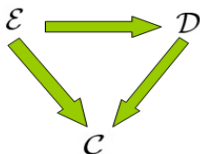
Mediator



Cases itself



Collider



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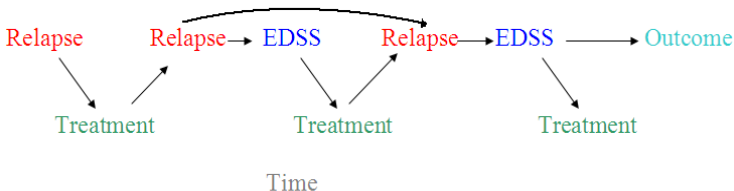
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Why fancy modelling > Over-Adjustment



- Relapse is both **confounder** and **mediator** variable.
- Need to adjust for confounder, but adjusting for a mediator variable will **over-adjust/block causal path** [Hernán et al., 2004].

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Treatment Selection Model: $A(j) \sim \bar{A}(j-1), V, \bar{L}(j)$

Weight Model:

$$SW(t) = \prod_{j=1}^t \frac{Pr(A(j)|\bar{A}(j-1), V)}{Pr(A(j)|\bar{A}(j-1), V, \bar{L}(j))}$$

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MSM Cox:

$$\lambda_{T_{\bar{a}}}(t|V) = \lambda_0 \times \exp(\beta_1 a(t) + \beta_2 V)$$

Hazard

Hazard
at baseline

Treatment
at time t

Baseline
covariates

- (1) Gender,
- (2) Age,
- (3) Disease duration

with weights $SW(t)$ (adjusting for time-dependent covariates)
[Robins, 1999; Hernán et al., 2000; Robins et al., 2000].

Still need to check the assumptions behind this model.

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Need to be very cautious while

- analyzing and
- interpreting results

from **observational** data,

especially while dealing with *time-dependent* variables.

References

- A. Coles. Multiple sclerosis: The bare essentials. *Neurology in practice*, 9 (2):118–126, 2009.
- M.Á. Hernán, B. Brumback, and J.M. Robins. Marginal structural models to estimate the causal effect of zidovudine on the survival of HIV-positive men. *Epidemiology*, 11(5):561, 2000. ISSN 1044-3983.
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- J.M. Robins. Association, causation, and marginal structural models. *Synthese*, 121(1):151–179, 1999. ISSN 0039-7857.
- J.M. Robins, M.Á. Hernán, and B. Brumback. Marginal structural models and causal inference in epidemiology. *Epidemiology*, 11(5):550, 2000. ISSN 1044-3983.
- H. Tremlett, M. Yousefi, V. Devonshire, P. Rieckmann, and Y. Zhao. Impact of multiple sclerosis relapses on progression diminishes with time. *Neurology*, 73(20):1616–1623, 2009.

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Thank You!

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