Absolute Risk integration using penalized logistic regression

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  - Parametric models

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- Want to easily model non-proportional hazards. [1]
- A streamlined approach for reaching a **smooth absolute risk** curve. [1]

Dr. Cox's perspective

Reid: How do you feel about the cottage industry that's grown up around it [the Cox model]?
Cox: Don't know, really. In the light of some of the further results one knows since, I think I would normally want to tackle problems parametrically, so I would take the underlying hazard to be a Weibull or something. I'm not keen on nonparametric formulations usually.
Reid: So if you had a set of censored survival data today, you might rather fit a parametric model, even though there was a feeling among the medical statisticians that that wasn't quite right.
Cox: That's right, but since then various people have shown that the answers are very insensitive to the parametric formulation of the underlying distribution [see, e.g., Cox and Oakes, Analysis of Survival Data, Chapter 8.5]. And if you want to do things like predict the outcome for a particular patient, it's much more convenient to do that parametrically.

PatientID ScrArm Follow.Up.Time DeadOfPrCa

Recall

- **Using the ERSPC dataset and casebase, we will determine Justin's absolute risk for death by prostate cancer.**

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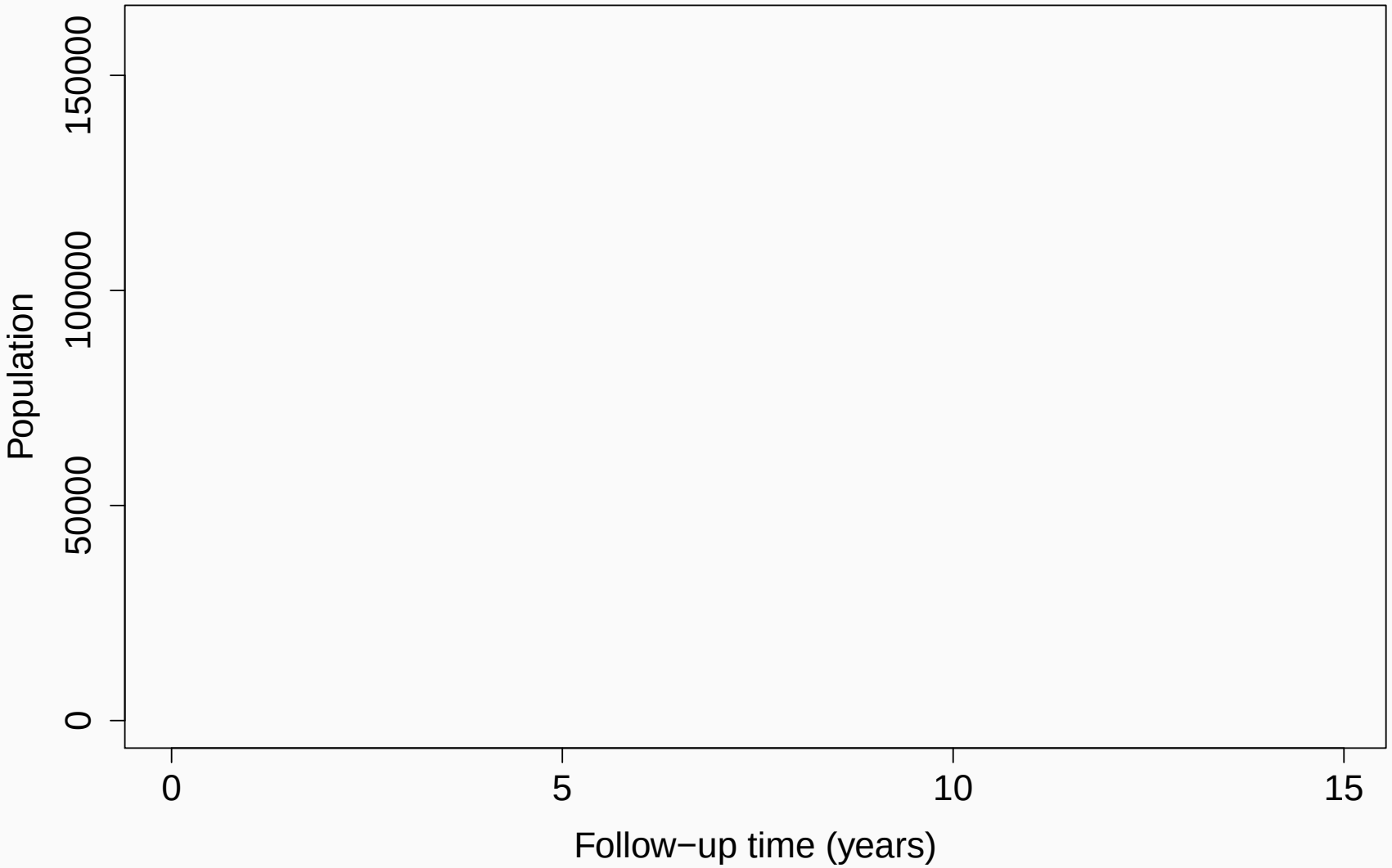
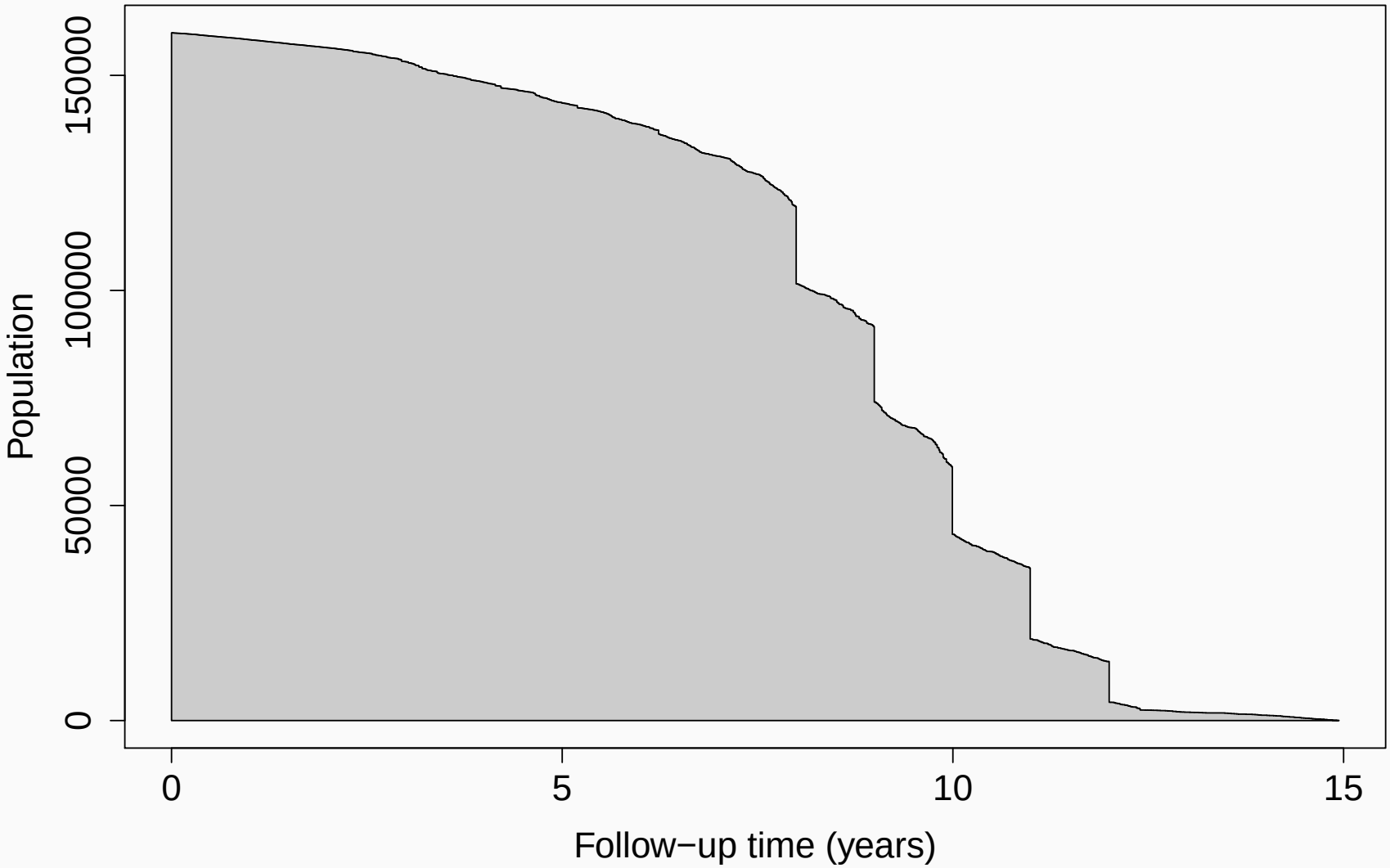
- Casebase is parametric, and allows different parametric fits by incorporation of the time component.
- Package contains an implementation for generating *population-time* plots.

Casebase: Sampling



Casebase: Sampling



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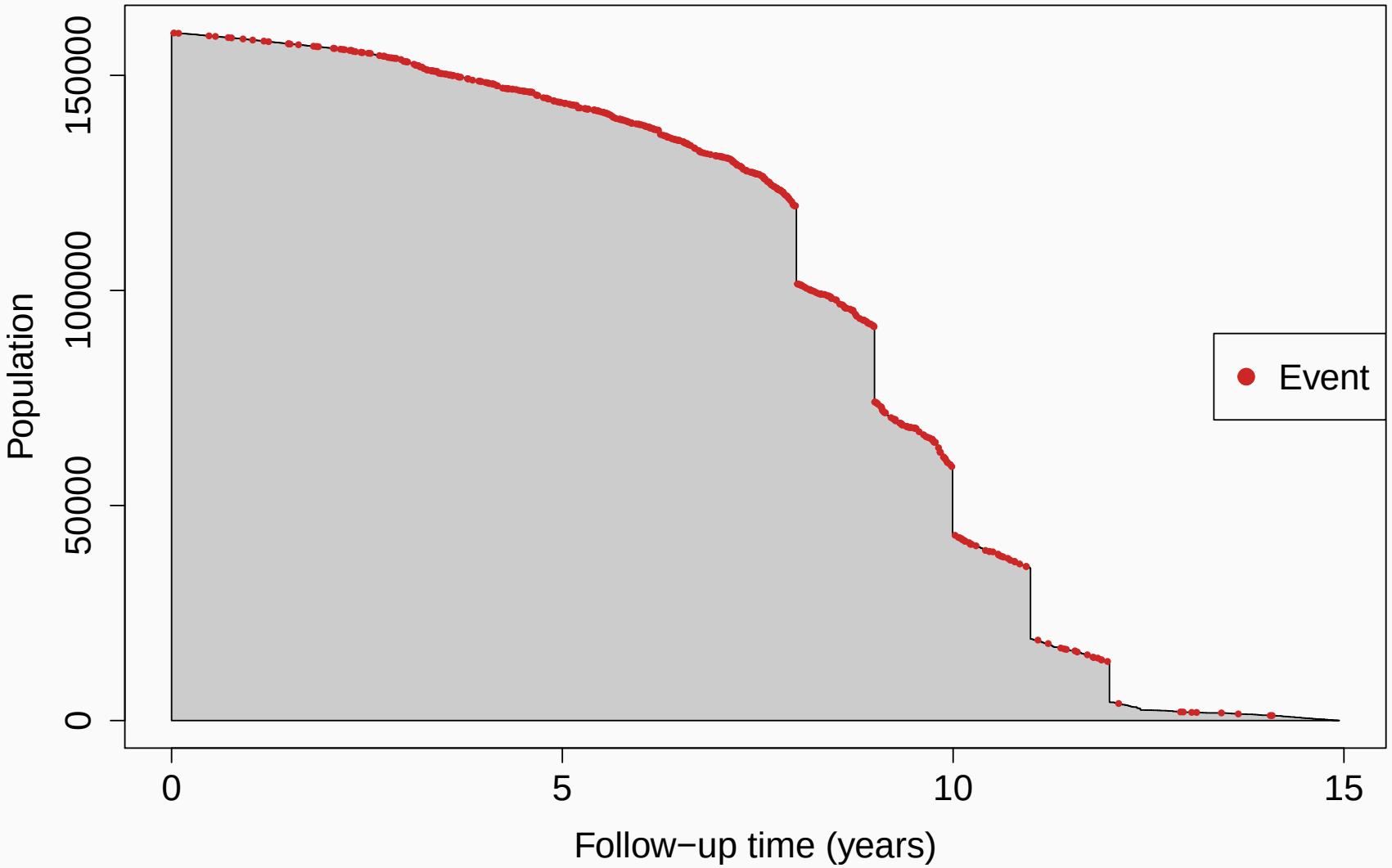
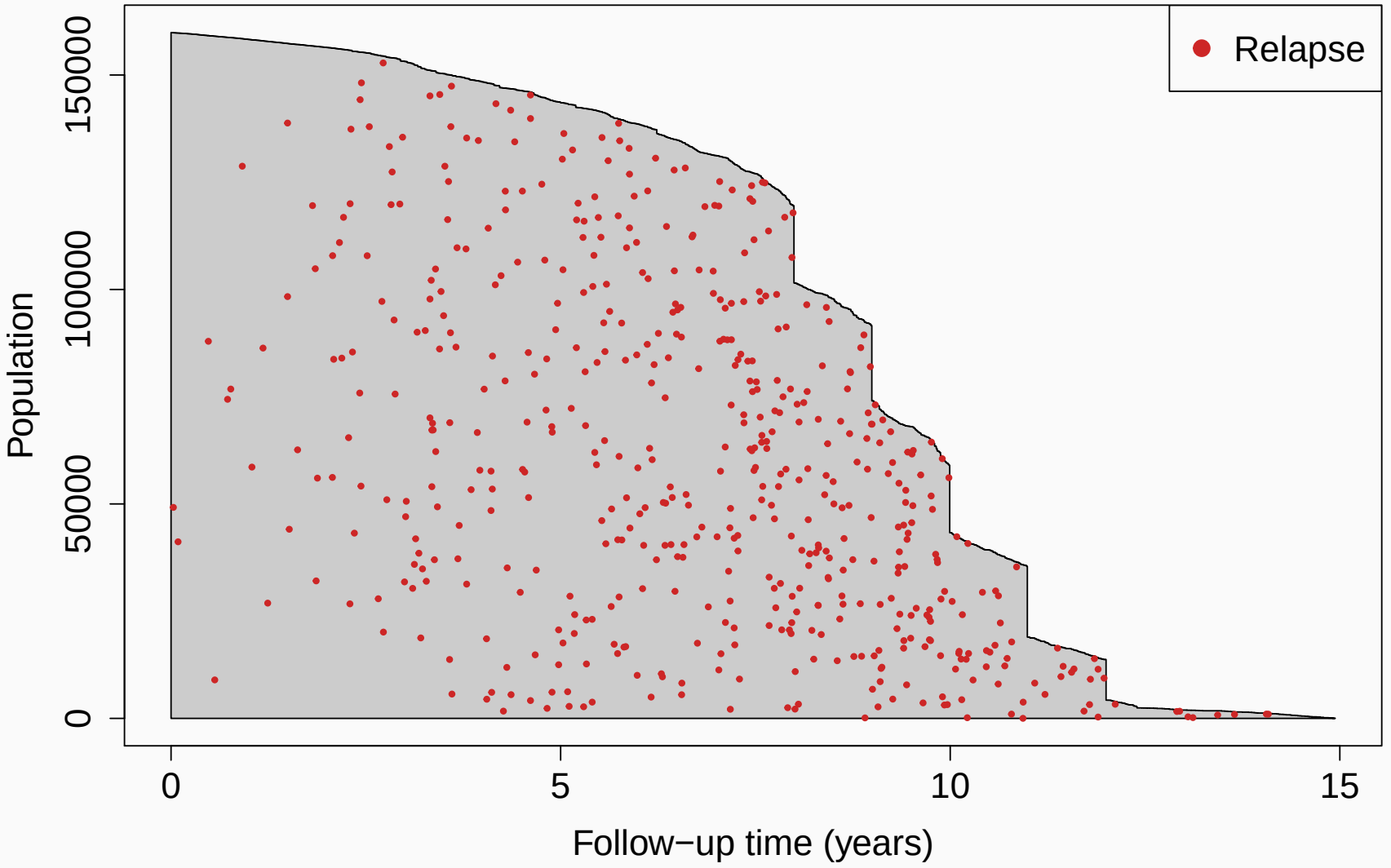


Casebase: Sampling

```
casebase::popTime(Data,Event,Time)
```



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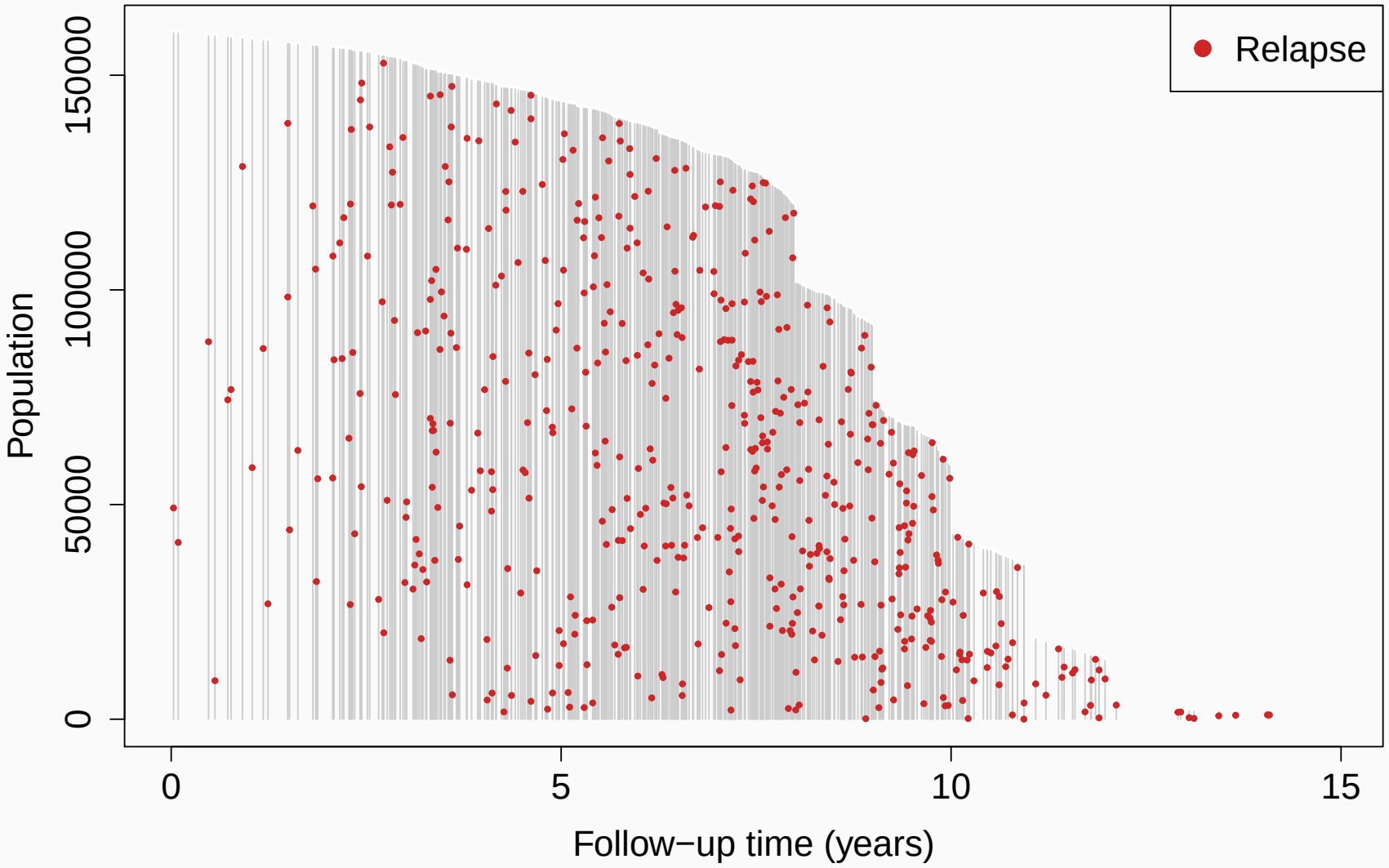

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$$log(h(t; \alpha, \beta)) = g(t; \alpha) + \beta X$$

- By changing the function $g(t; \alpha)$, we can model different parametric families easily:

Casebase: Parametric models

Exponential: $g(t; \alpha)$ is equal to a constant

```
casebase::fitSmoothHazard(status ~ X1 + X2)
```

Gompertz: $g(t; \alpha) = \alpha t$

```
casebase::fitSmoothHazard(status ~ time + X1 + X2)
```

Weibull: $g(t; \alpha) = \alpha log(t)$

```
casebase::fitSmoothHazard(status ~ log(time) + X1 + X2)
```

Death by prostate cancer: hazard ratios

```
casebase::fitSmoothHazard(DeadOfPrCa~ log(Follow.Up.Time)+
                                ScrArm, data=ERSPC, ratio = 100)
```

ERSPC Hazard comparison

Model	Hazard Ratio	Std.Error
Cox	0.801	1.092
Gompertz	0.802	1.093
Exponential	0.810	1.092
Weibull	0.797	1.093

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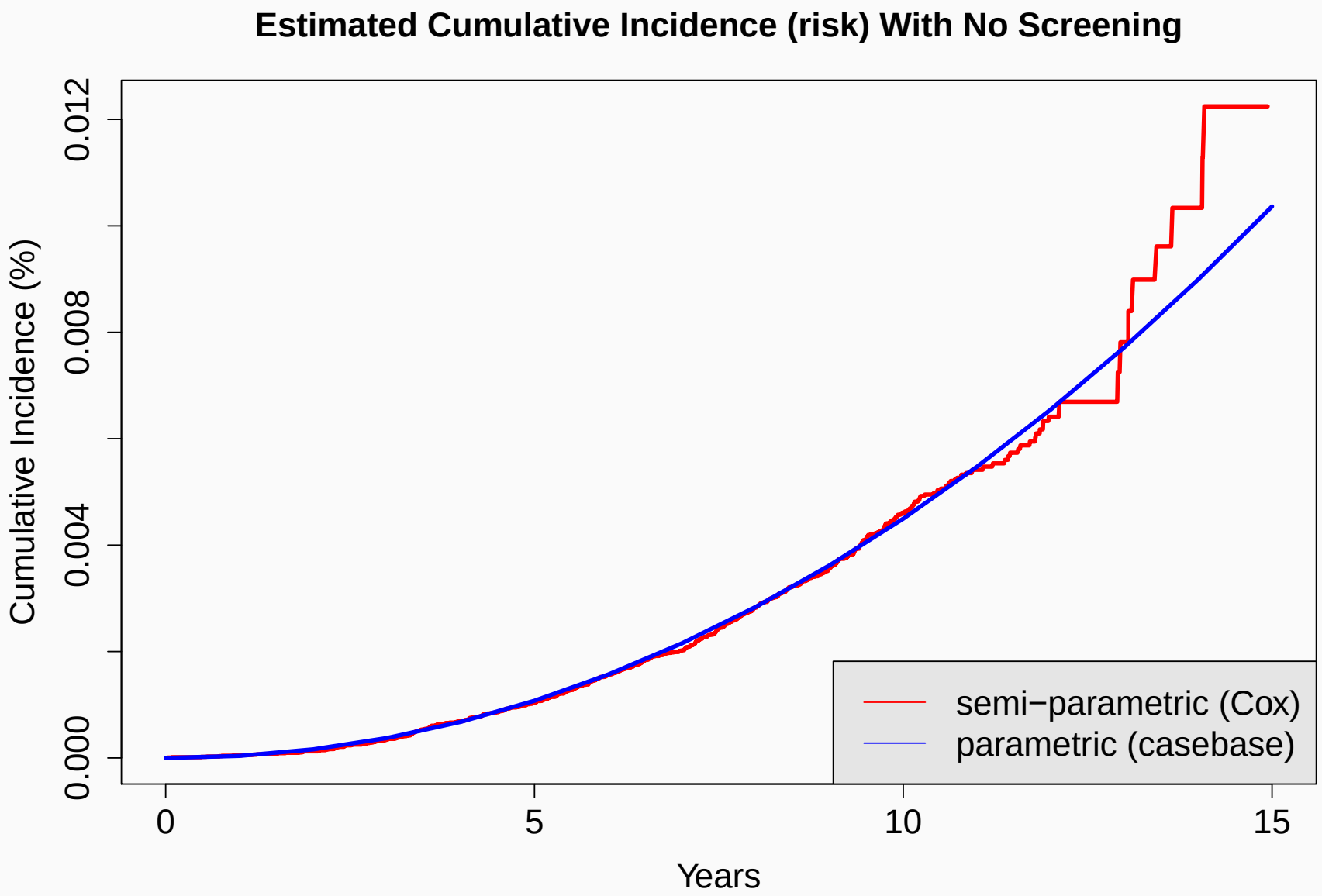
- $h(x,u)$= Hazard function
- Lets use the weibull hazard

Casebase: Absolute Risk comparison

```
casebase::absoluteRisk(fit, time=5, covariate_profile)
```



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- The casebase package contains tools to generate:
  - Population-Time plots
  - Hazard functions
  - Absolute Risk
  - Casebase can deal with competing risks.

References 1

1.Hanley, James A, and Olli S Miettinen. 2009. "Fitting Smooth-in-Time Prognostic Risk Functions via Logistic Regression." *The International Journal of Biostatistics 5 (1)*.

2.Saarela, Olli, and Elja Arjas. 2015. "Non-Parametric Bayesian Hazard Regression for Chronic Disease Risk Assessment." Scandinavian Journal of Statistics 42 (2). Wiley Online Library: 609–26.

3.Saarela, Olli. 2015. "A Case-Base Sampling Method for Estimating Recurrent Event Intensities." *Lifetime Data Analysis*. Springer, 1–17

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4.Schroder FH, et al., for the ERSPC Investigators.Screening and Prostate-Cancer Mortality in a Randomized European Study. *N Engl J Med* 2009;360:1320-8.

5.Scrucca L, Santucci A, Aversa F. Competing risk analysis using R: an easy guide for clinicians. *Bone Marrow Transplant*. 2007 Aug;40(4):381-7. doi: 10.1038/sj.bmt.1705727.

6.Turgeon, M. (2017, June 10). Retrieved May 05, 2019, from https://www.maxturgeon.ca/slides/MTurgeon-2017-Student-Conference.pdf

Tutorial and Slides

Tutorial:

http://sahirbhatnagar.com/casebase/

Slides:

https://github.com/Jesse-Islam/UseR–CaseBase-Presentation

Questions?