Absolute Risk integration using penalized logistic regression

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- When we want the absolute risk:
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  - Parametric models

Motivations for a new method

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- They believe the stepwise nature is the reason, as it reduces interpretability. [1]
- 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.

Index

- SUPPORT study

Index

- SUPPORT study
- Casebase sampling

Index

- SUPPORT study
- Casebase sampling
- Logistic regression on survival data

Index

- SUPPORT study
- Casebase sampling
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- Maximum likelihood with regularization

Index

- SUPPORT study
- Casebase sampling
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Index

Index

- SUPPORT study
- Casebase sampling
- Logistic regression on survival data
- Maximum likelihood with regularization
- Comparing hazard models in SUPPORT study
- Absolute risk comparison
- Future work

Index

SUPPORT dataset

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- **Study to Understand Prognoses and Preferences for Outcomes and Risks Treatments**
- Design: Prospective cohort study.
- Setting: 5 academic care centers in the United States
- Participants: 4301 hospitalized adults, (only have access to 1000)
- Follow-up-time: 180 days

SUPPORT Imputation

- Notorious for missing data

Baseline Variable	Normal Fill-in Value
Bilirubin	1.01
BUN	6.51
Creatinine	1.01
PaO2/FiO2 ratio (pafi)	333.3
Serum albumin	3.5
Urine output	2502
White blood count	9 (thousands)

Table 1: Suggested imputation values. [Support site reference]

Casebase Overview

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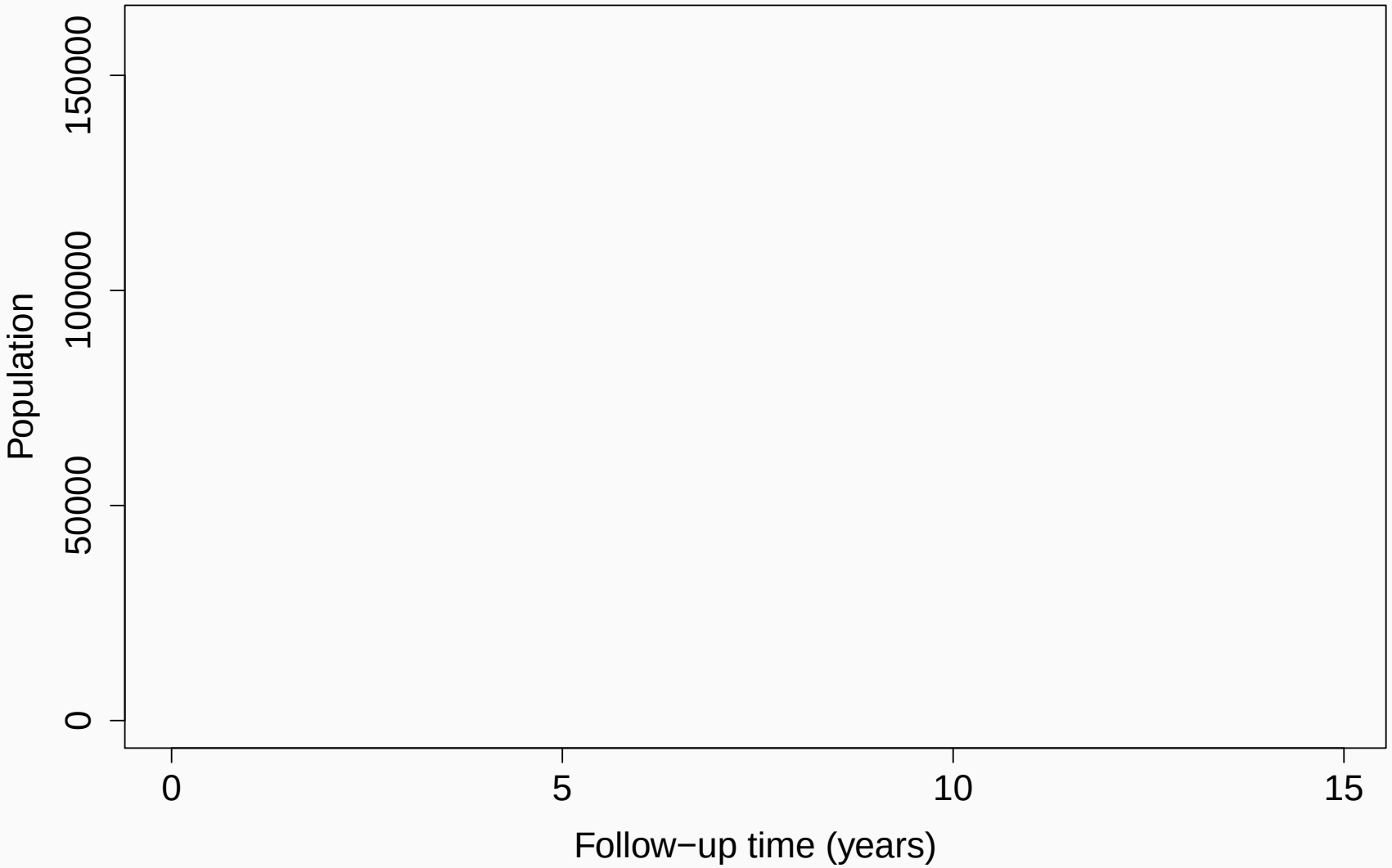
- Casebase is parametric, and allows different parametric fits by incorporation of the time component.
- Package contains an implementation for generating *population-time* plots.

Casebase: Sampling



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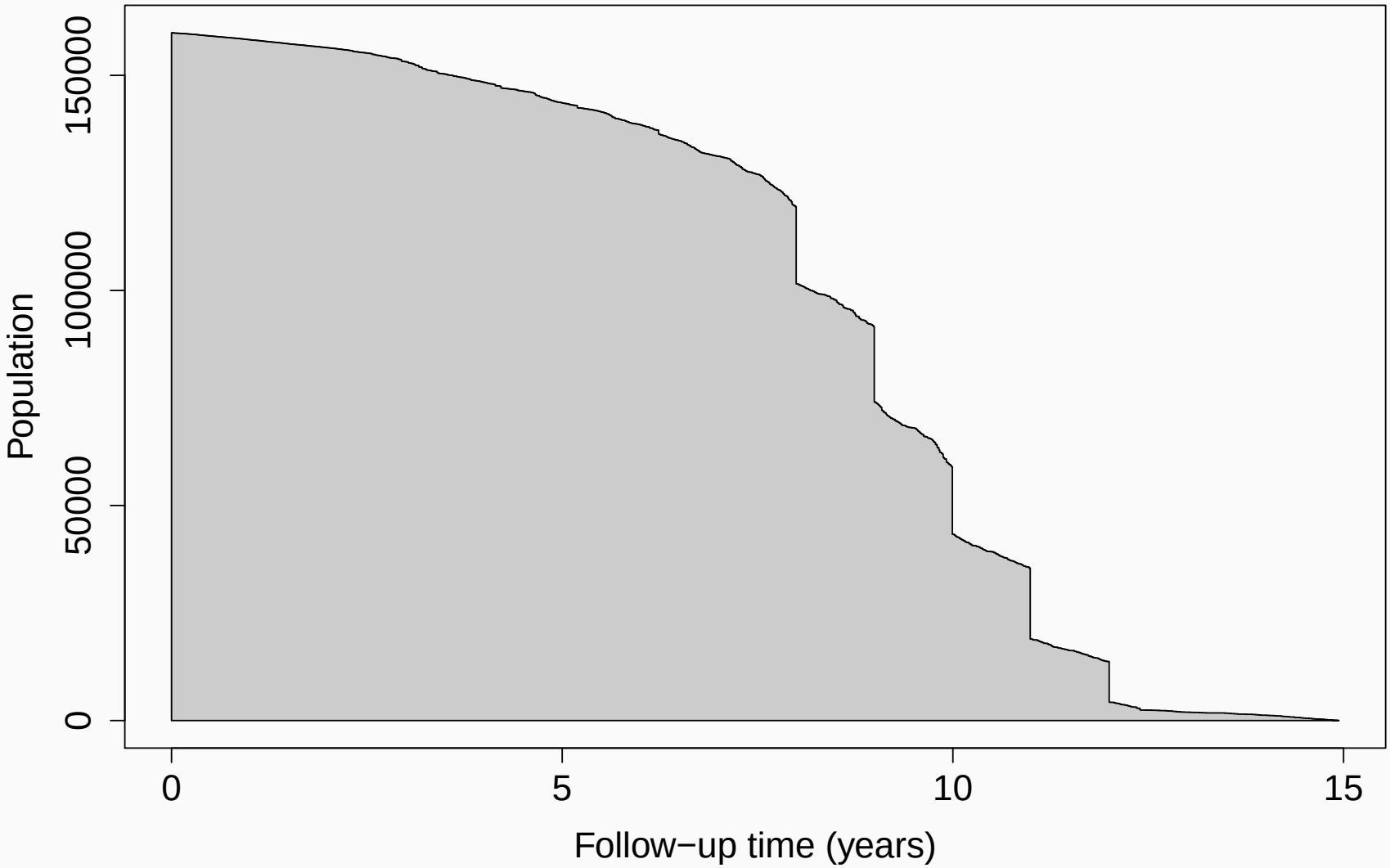

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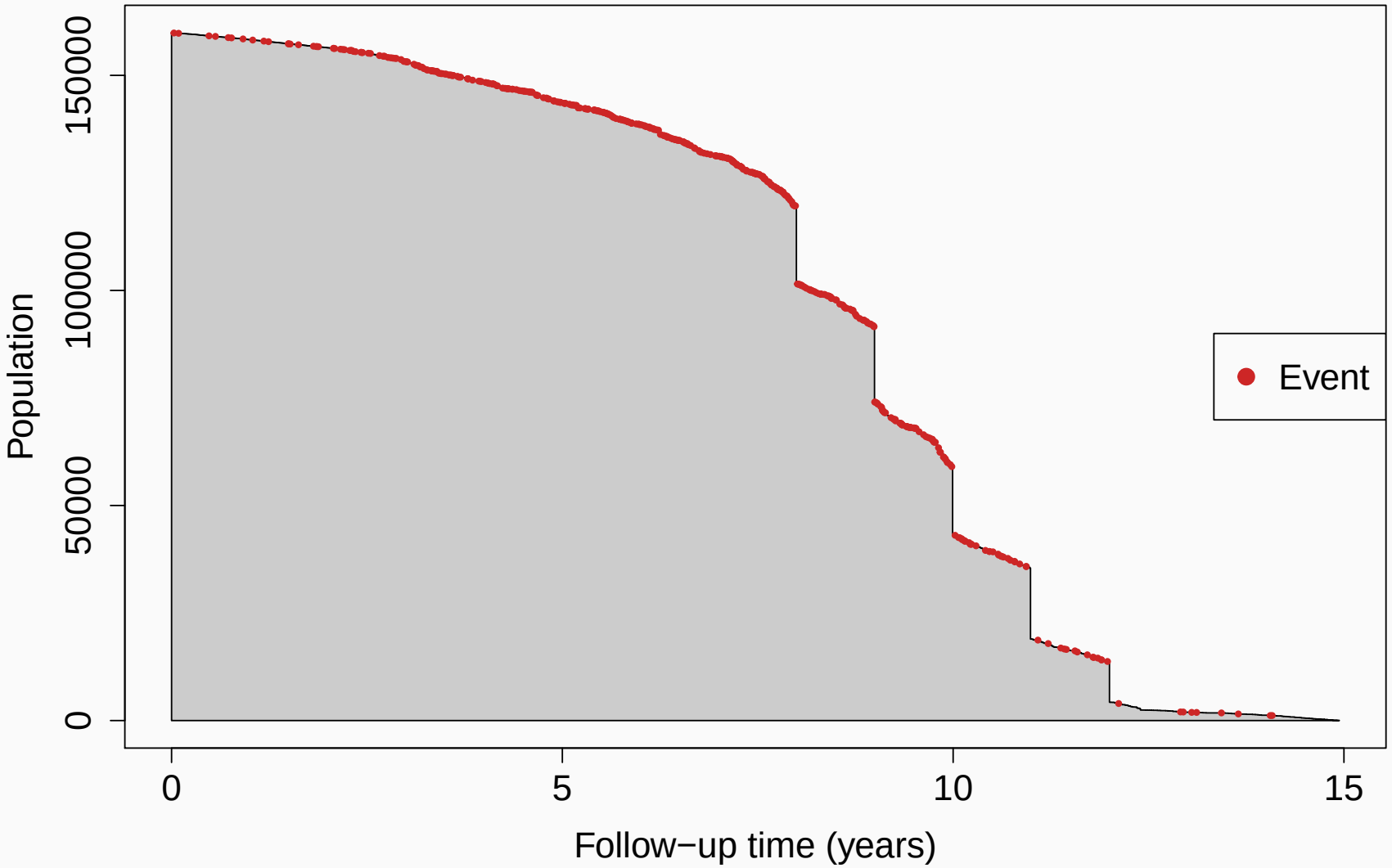
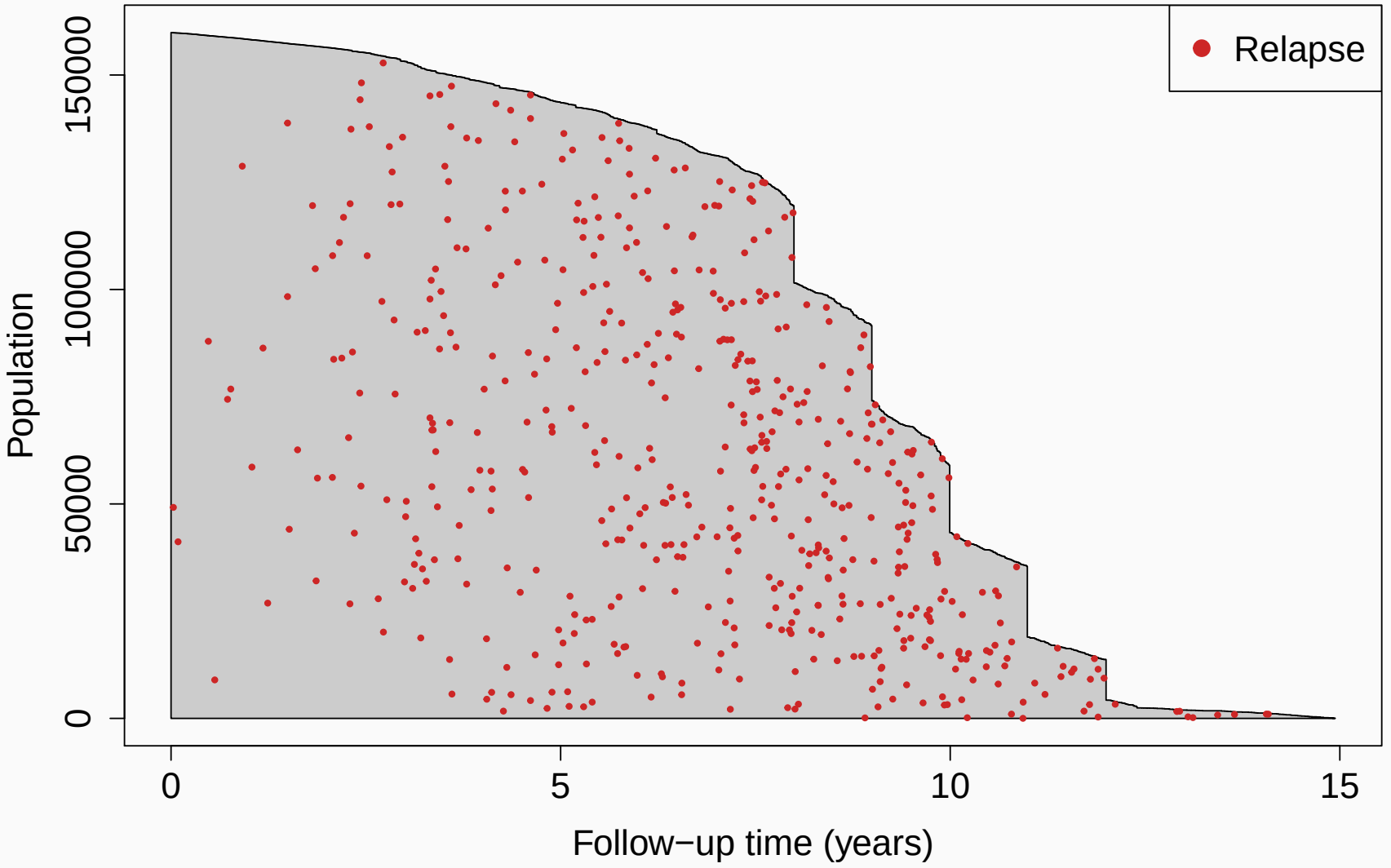


Casebase: Sampling

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



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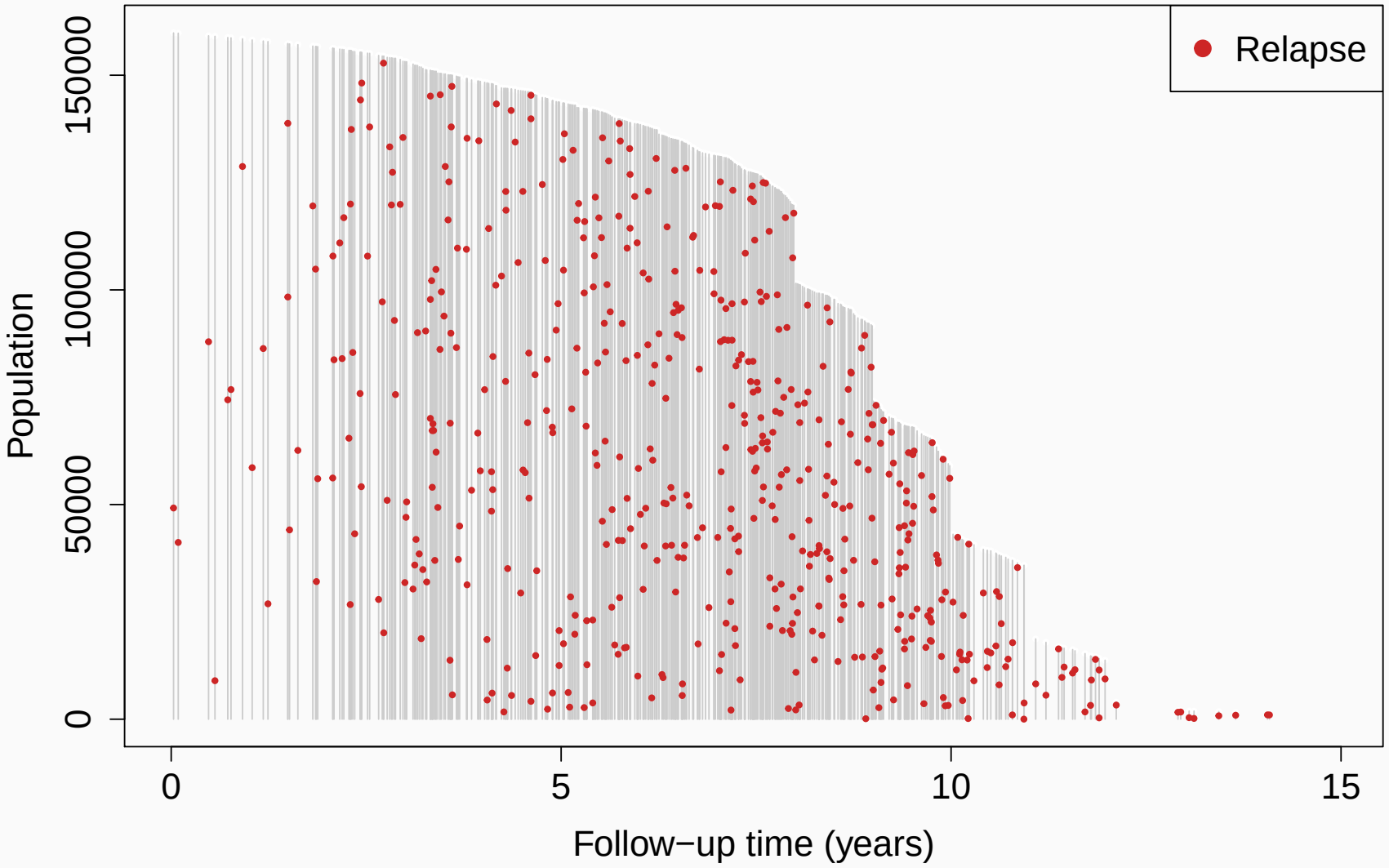

Casebase: Parametric families

- We can now fit models of the form:

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

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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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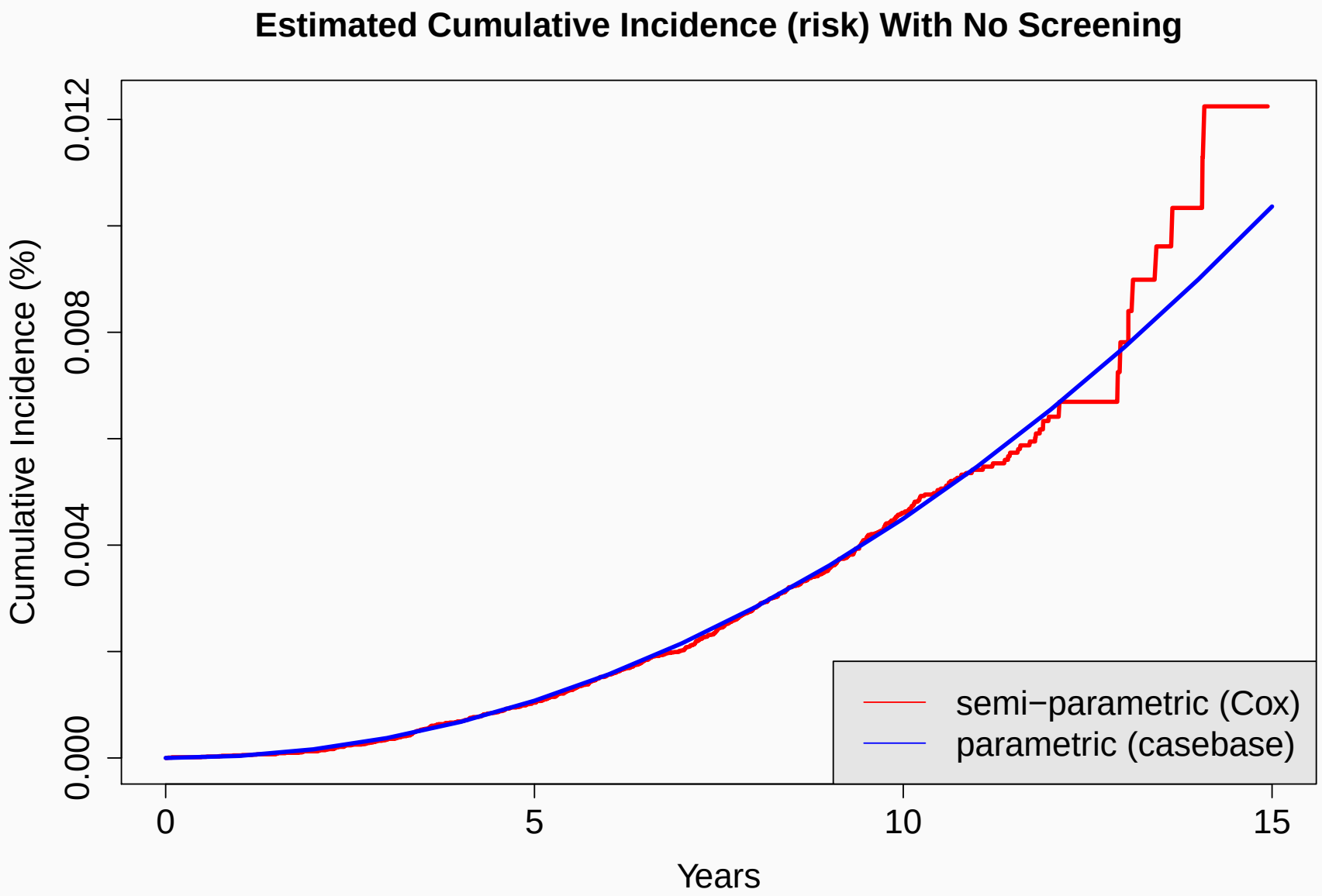
- $CI(x,t)$= Cumulative Incidence (Absolute Risk)
- $h(x,u)$= Hazard function
- Lets use the weibull hazard

Casebase: Absolute Risk comparison

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



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- Casebase sampling implicitly incorporates censoring and permits the use of GLMs and the tools associated with them
- The casebase package contains tools to generate:
  - Population-Time plots
  - Hazard functions
  - Absolute Risk
  - Casebase can deal with competing risks.

References 1

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Tutorial and Slides

Tutorial:

http://sahirbhatnagar.com/casebase/

Slides:

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

Questions?