



# Controlling time-varying confounding in a cohort of bone marrow transplant patients, a comparison of g-methods.



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## Introduction

**Graft-versus-Host-Disease (GvHD)** a serious side-effect of bone marrow transplant (BMT), also helps kill residual leukemia cells

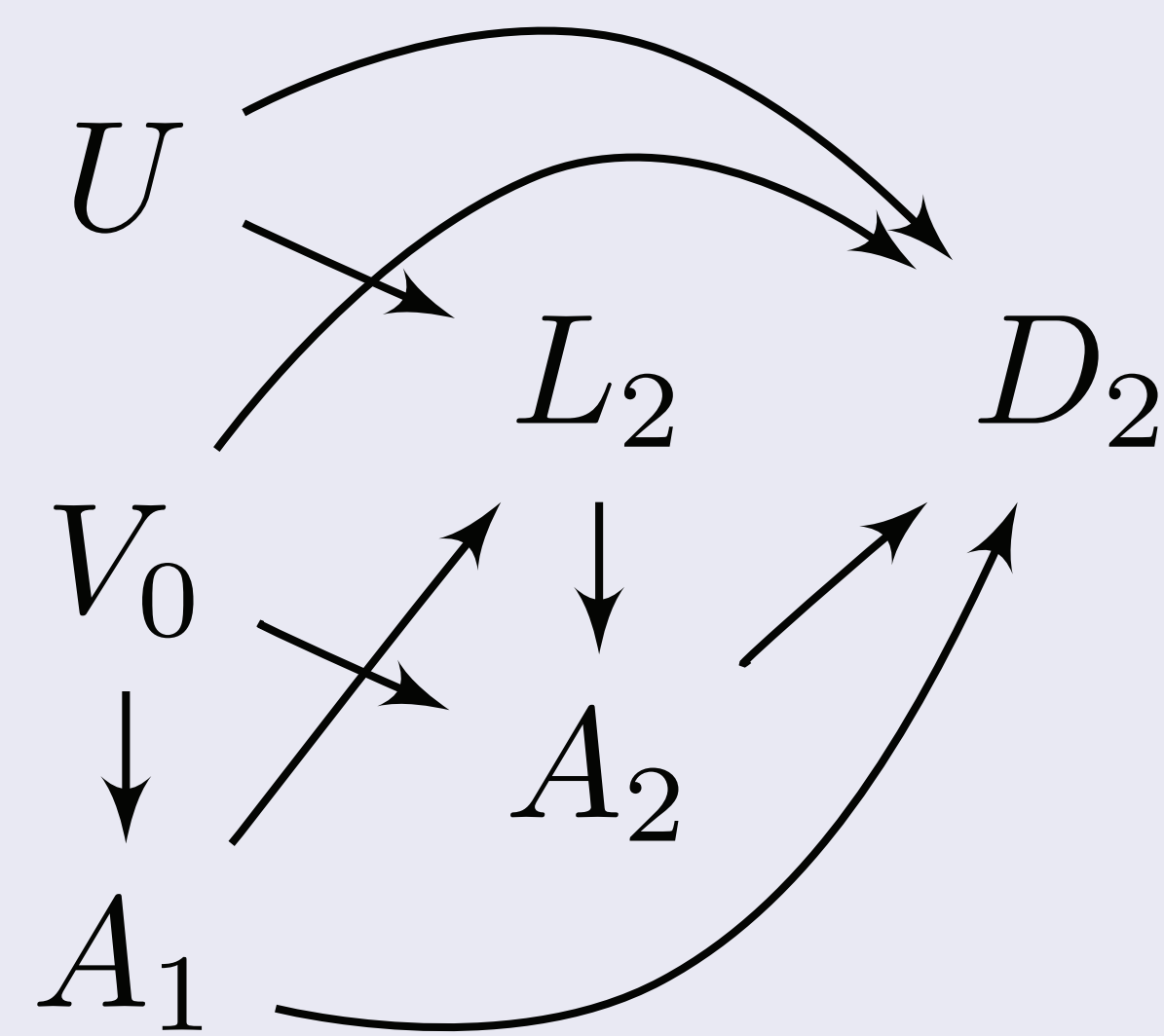
**Time varying confounding** for GvHD → mortality by platelet count and leukemia relapse (see figure 1)

**G-methods** can appropriately estimate effect of GvHD → mortality, choice between methods depends on causal knowledge

**Without causal knowledge** choice of methods is unclear

**137 bone marrow transplant patients** We estimate GvHD → mortality using 3 g-methods

## Causal graph



## Notation

$k=\{1,2,\dots\}$  subscript indexes time in days

$A_k$  GvHD at time k (yes or no)

$L_k$  Time varying confounders: relapse and platelet count (time varying confounders)

$V_0$  Baseline confounders: age (spline), sex, cytomegalovirus status (yes or no), leukemia type (AML vs. others), transplant wait time (linear)

$D_k$  Death between day k-1 and k

$T$  Time to all-cause mortality

## Methods

**G-formula** Using Monte Carlo approximation of parametric G-formula

- 1 Pooled logistic model: generate conditional probabilities of all covariates
- 2 Substitute probabilities under interventions
- 3 Resample data under probabilities to generate data under interventions

**Marginal structural mode** Fit via IP weighting

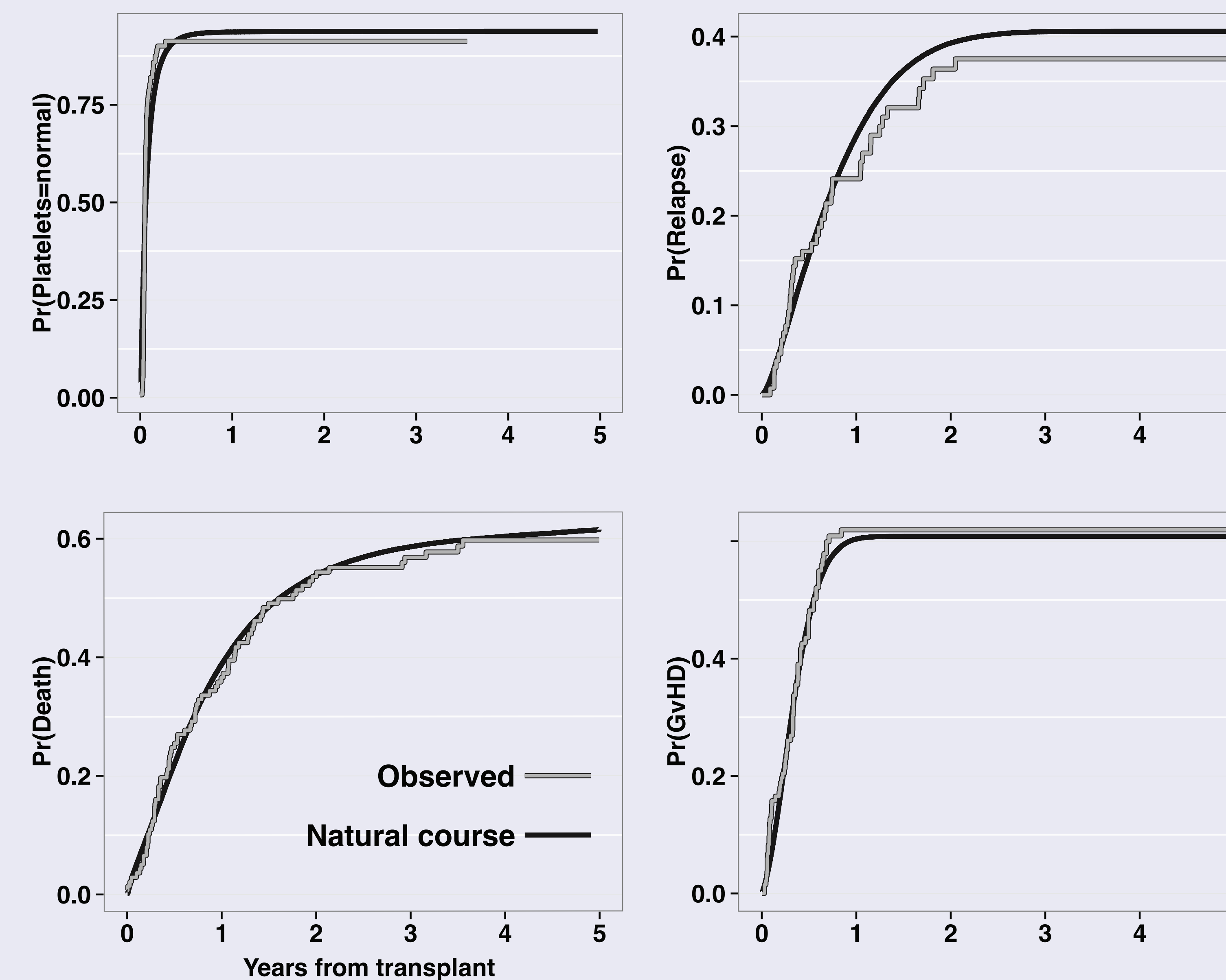
- 1 Pooled logistic model: generate conditional probabilities of GvHD
- 2 Inverse probability weight the data
- 3 Fit a marginal model to re-weighted data

**Structural nested accelerated failure time model** Fit via g-estimation

- 1 Propose a total effect of exposure (total effect= $\psi$ )
- 2 Generate  $T^*$  = residual outcome not due to exposure via  $T^* = \int_0^T \exp(GvHD_k \psi) dk$
- 3 Test  $Pr(GvHD_k | \text{prior confounders}, T^*) = Pr(GvHD | \text{prior confounders})$
- 4 Repeat 1-3 until exposure is not associated with “residual” outcome, that value of  $\psi$  is the estimate

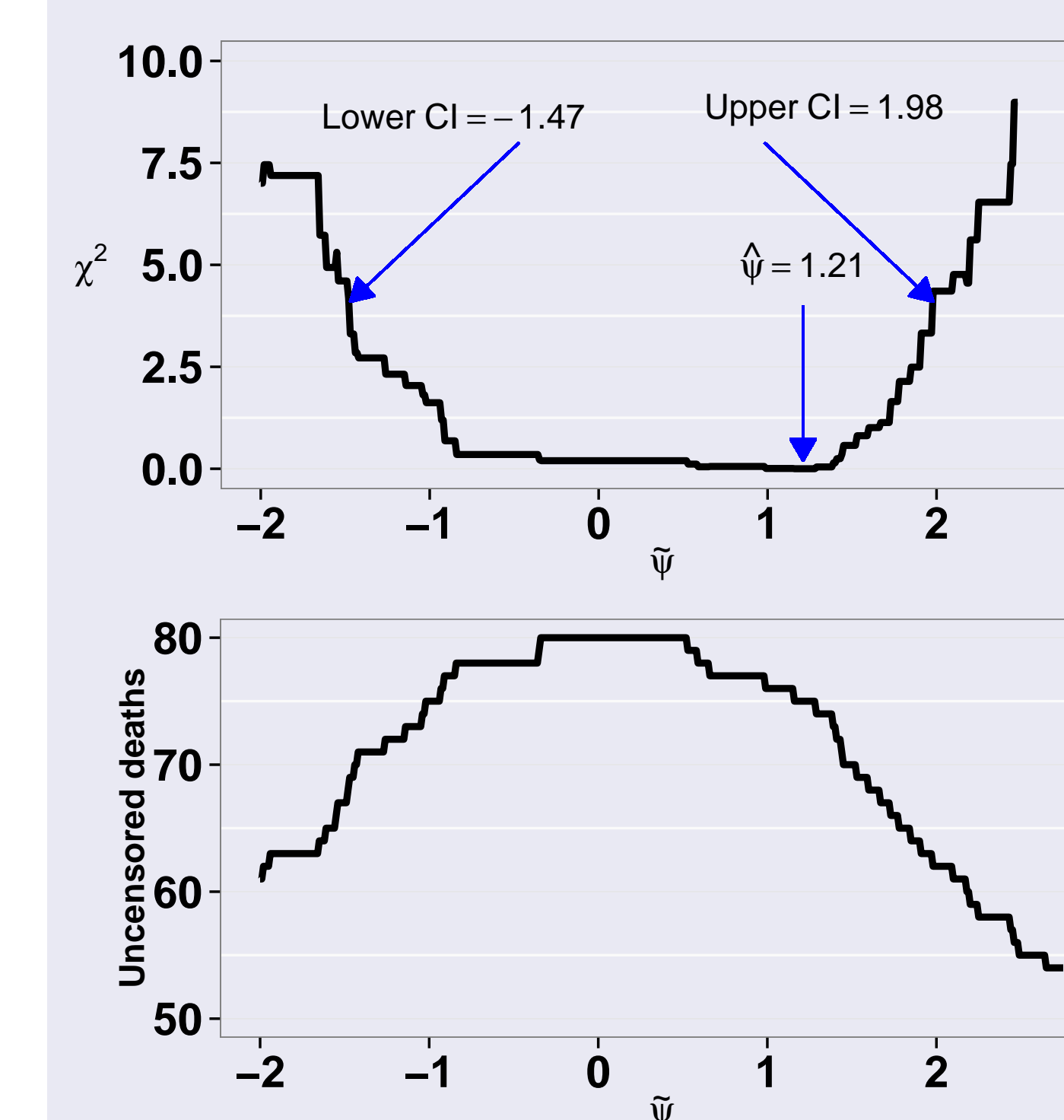
**Comparing methods** We generated HRs and 95% confidence intervals to compare 3 g-methods with standard Cox regression

## G-formula distributions



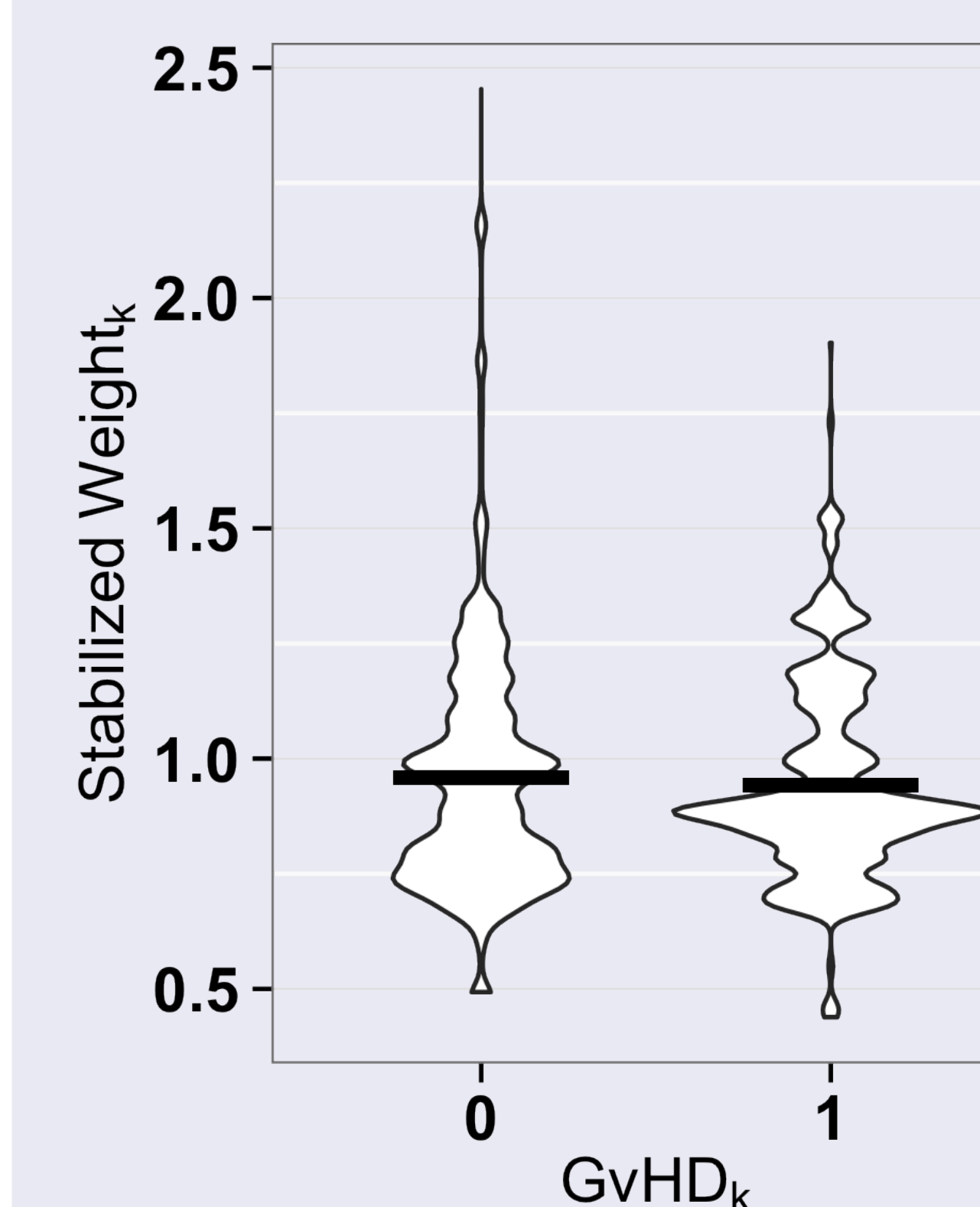
Distributions of time varying covariates: observed and G-formula under no intervention (natural course)

## SNAFTM g-function



The g-function (top panel) and number of uncensored deaths (bottom) as a function of the proposed total effect of GvHD on mortality

## MSM weights



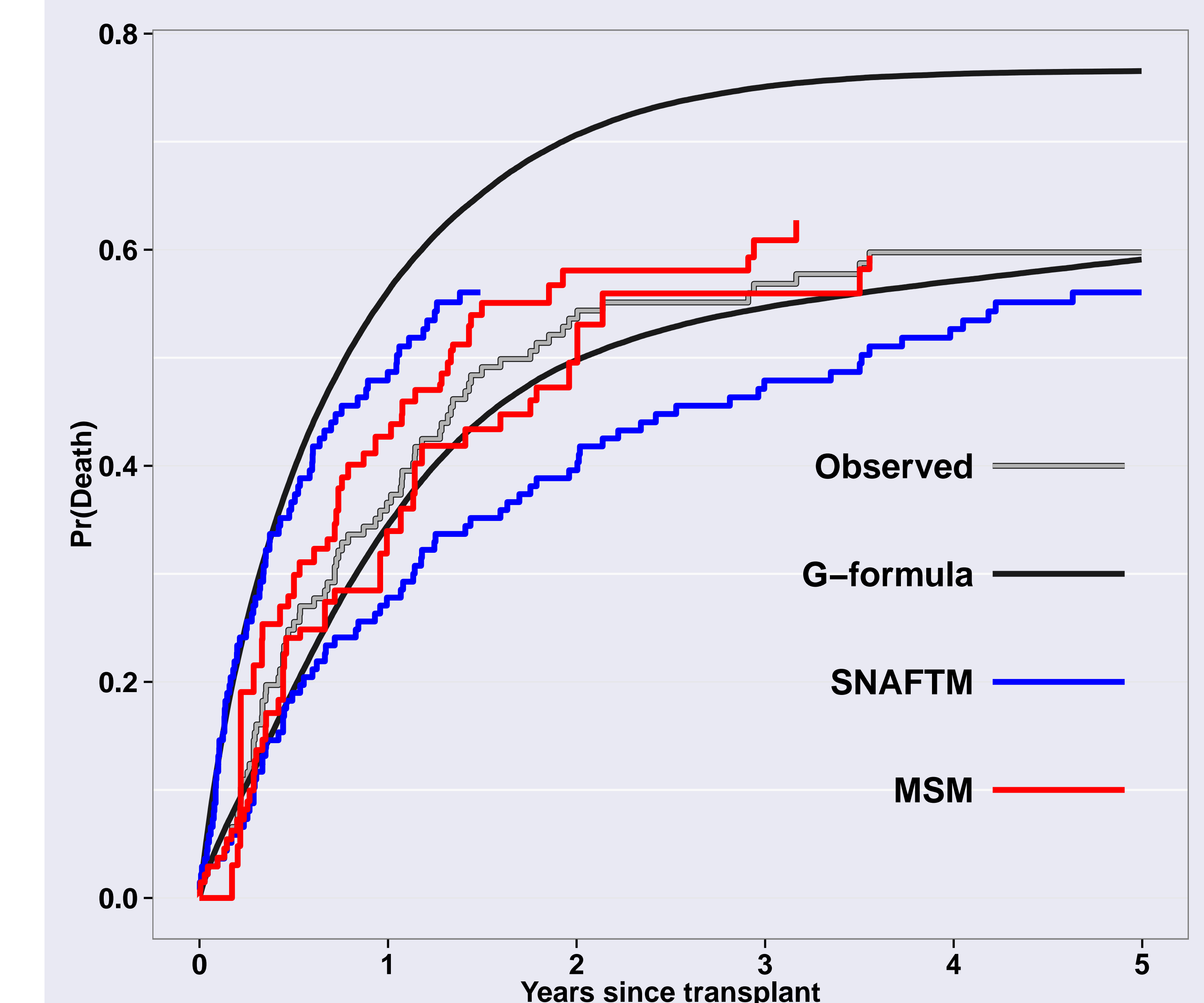
Distribution and mean of time specific weights used to fit marginal structural model.

## Hazard ratios

	Cox HR	95% CI
Crude	1.24	0.77, 2.00
Baseline adjusted	1.16	0.66, 2.03
Fully adjusted	2.36	1.30, 4.29
G formula	1.83	0.98, 3.40
MSM	1.18	0.70, 1.98
SNAFTM	2.00	

Hazard ratios, 95% confidence intervals from conventional Cox regression models and 3 g-methods on Bone Marrow Transplant data.

## Survival curves



Survival curves generated by method by GvHD (always - top three lines vs. never = bottom three lines)

## Conclusions

- Inverse probability weighting may be biased due to positivity violations
- Structural nested models relax restrictions but at a cost of efficiency
- In the absence of causal knowledge the g-formula is useful as a comparator to less modeling intensive methods

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