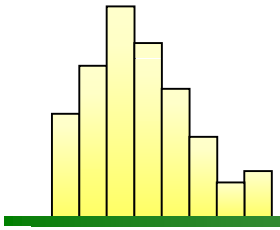
Discrete-time Survival Analysis using Latent Variables Part 2



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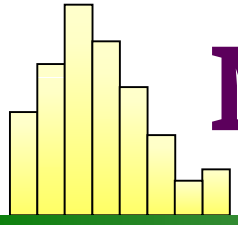


Multivariate event histories

- Recurrent events (multiple spells)

  Same outcome that may occur more than once

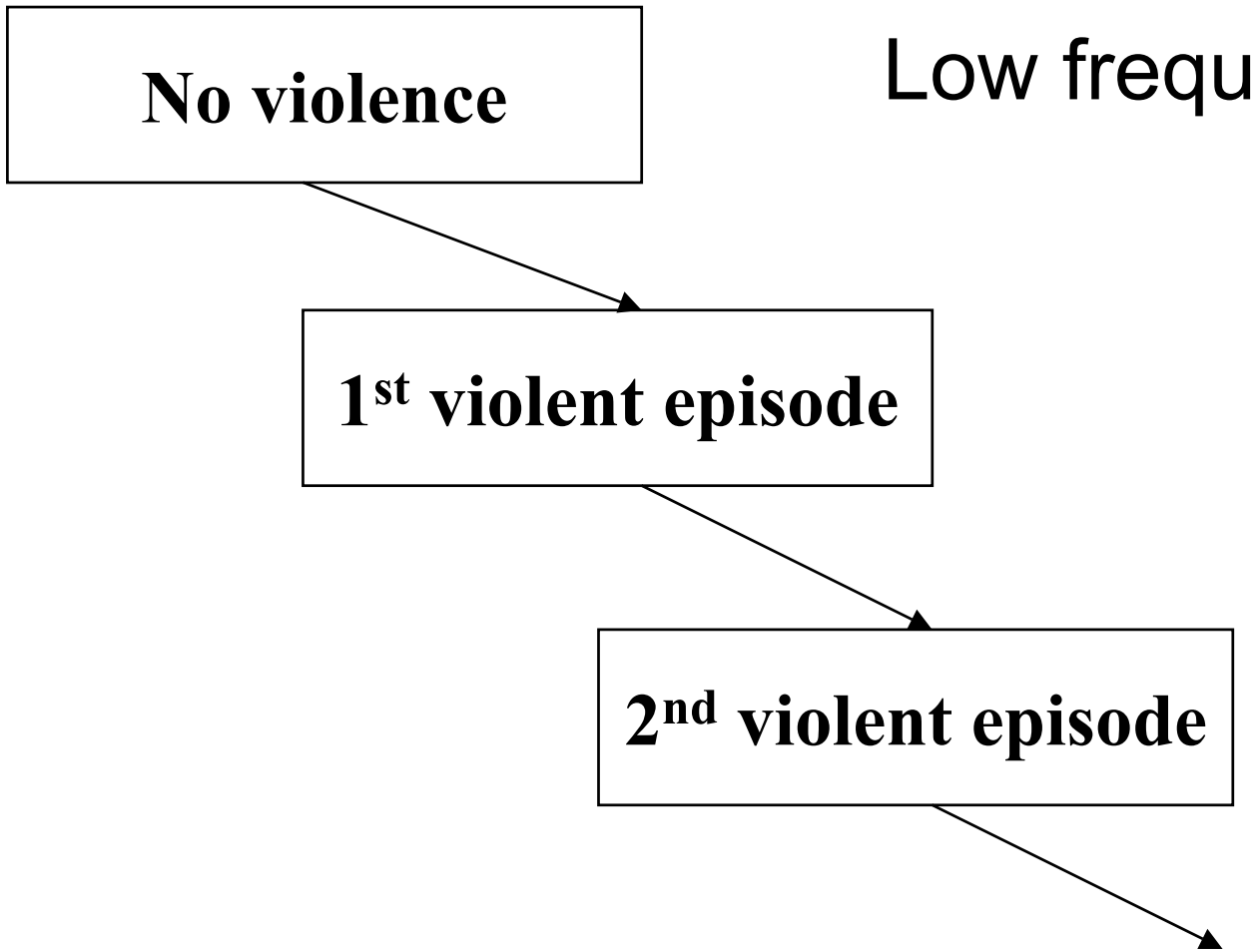
- Competing risks

  More than one possible outcome

- Parallel process

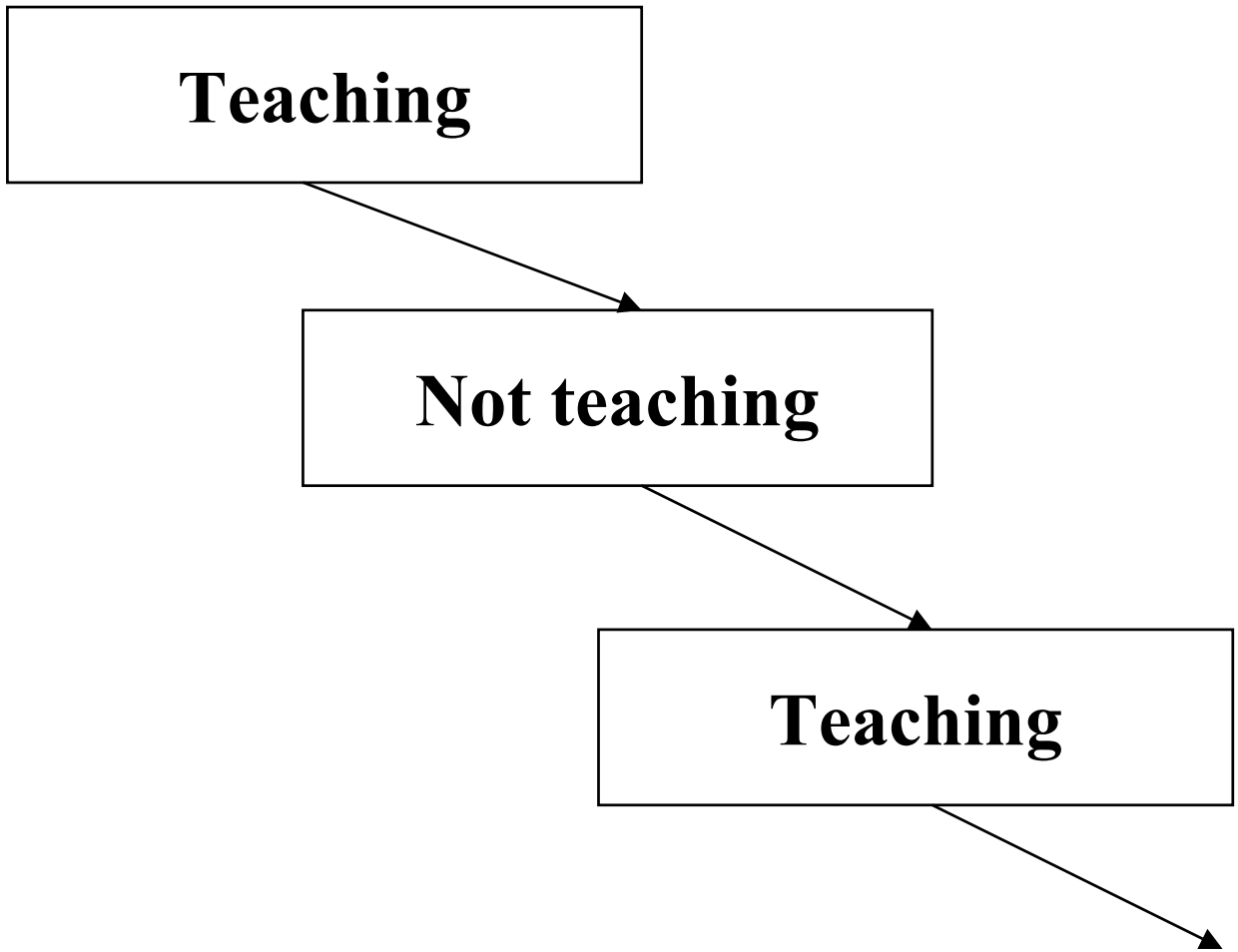
  Multiple event processes occurring at the same time with event-specific risk status

Recurrent events example



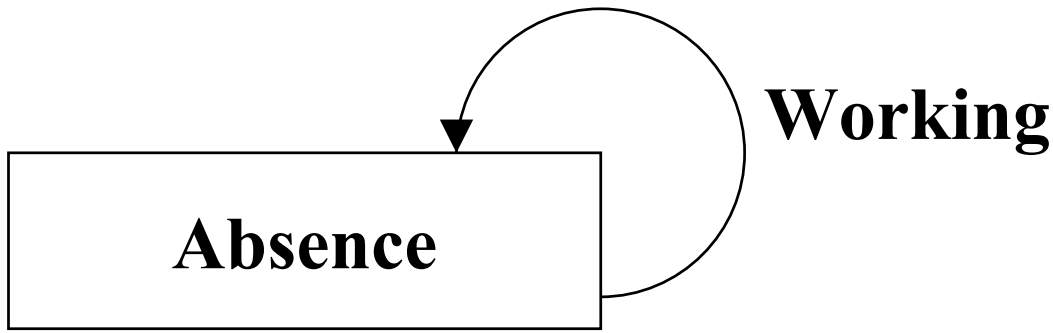
Low frequency

Multiple spells example

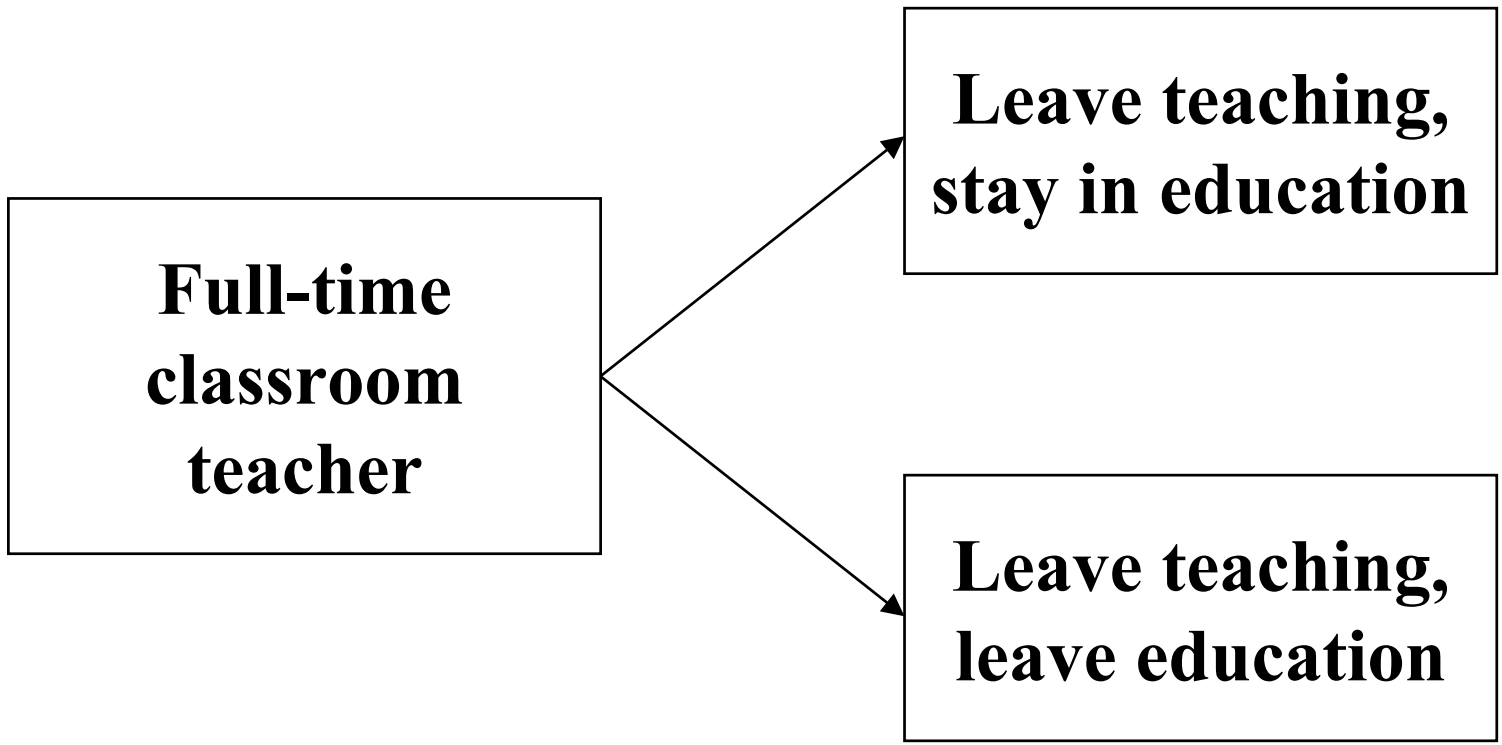


Recurrent events example

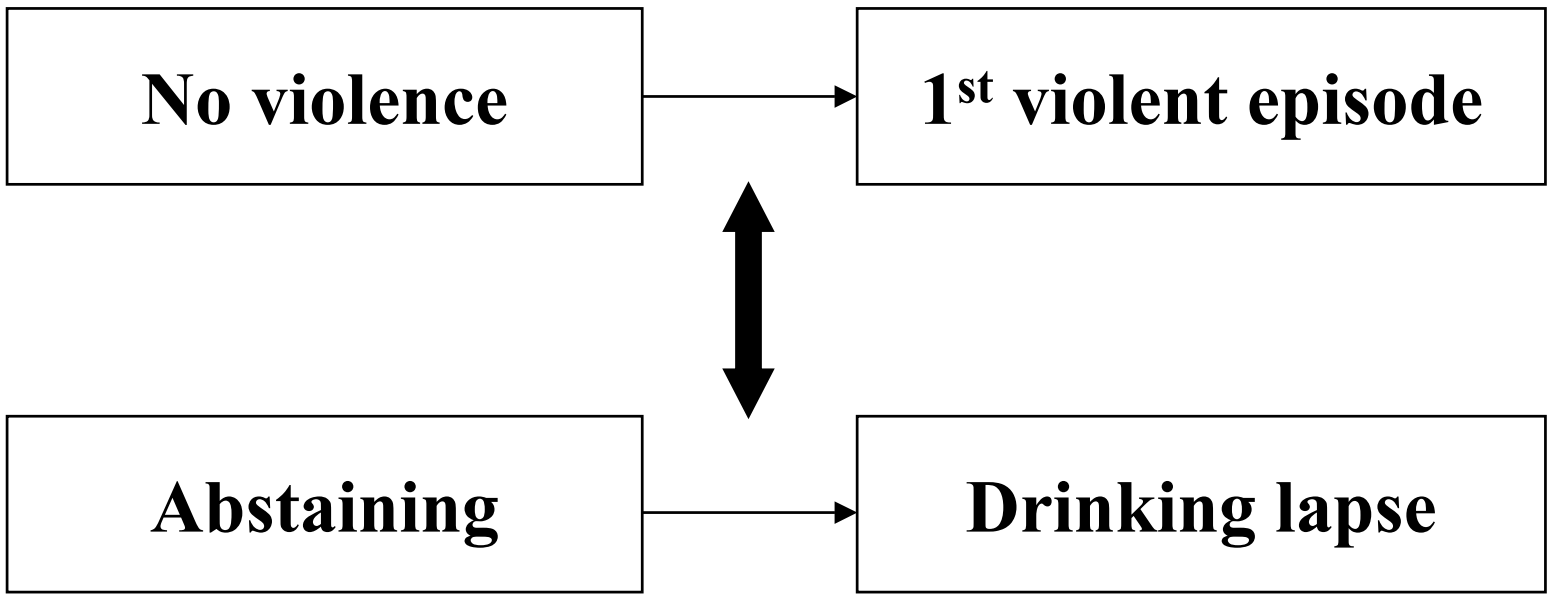
High frequency

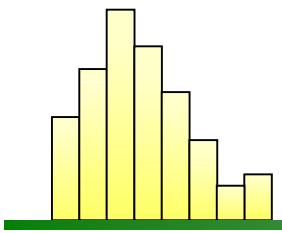


Competing risks example



Parallel processes example





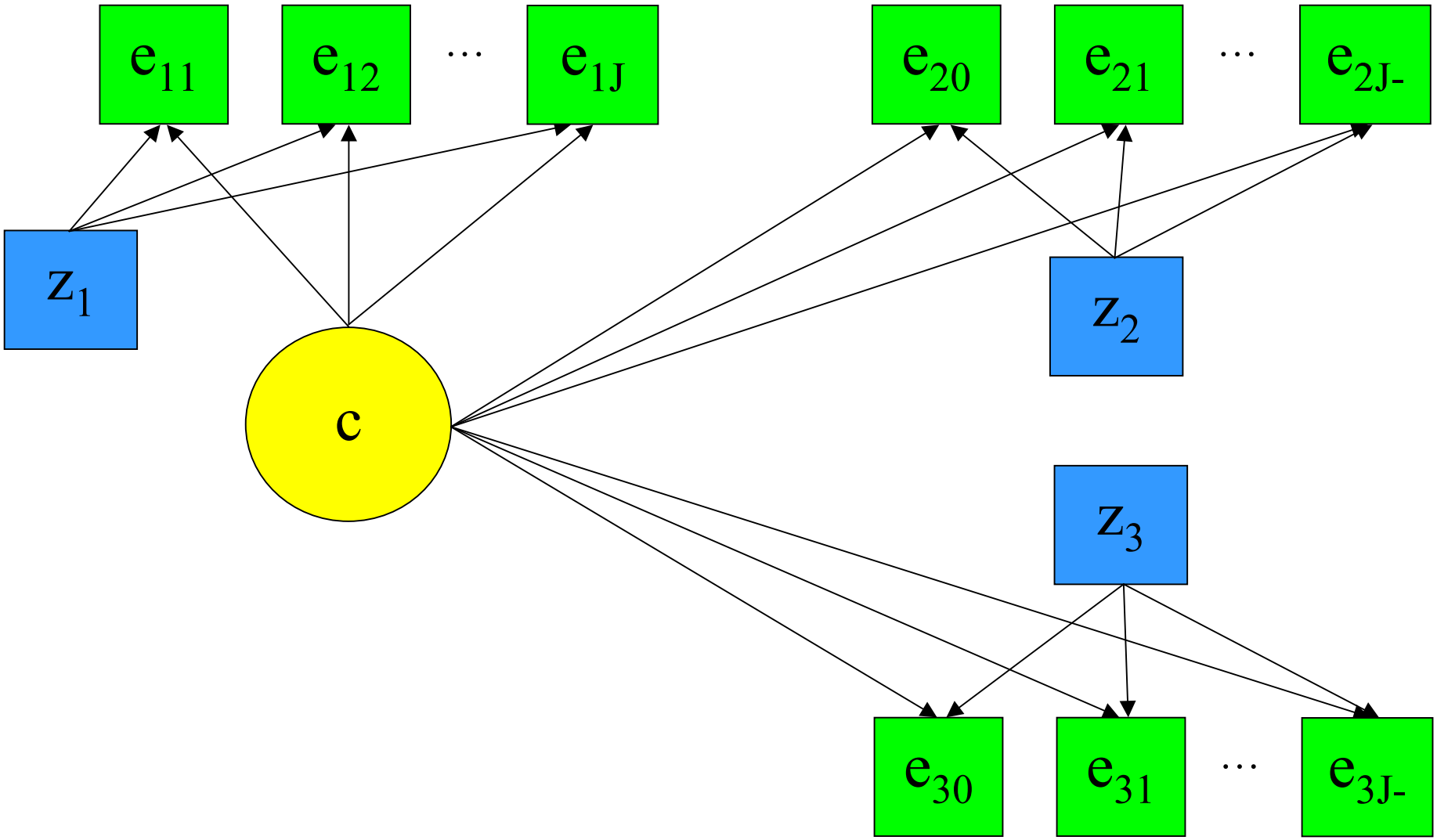
Low-frequency recurrent event process features

- Individuals are only at-risk for one event at a time
- Individuals may not be at-risk for event *m* until after the occurrence of *m-1*
- Event times correlated within individuals
- Event-specific baseline hazard probabilities and covariate effects

	0	*1*	*2*	*3*	*4*	*5*	*6*
E		0	0	1,2	0	3	0
E		0	0	0	1	0	0
E		0	0	0	0	0	0

Gap time

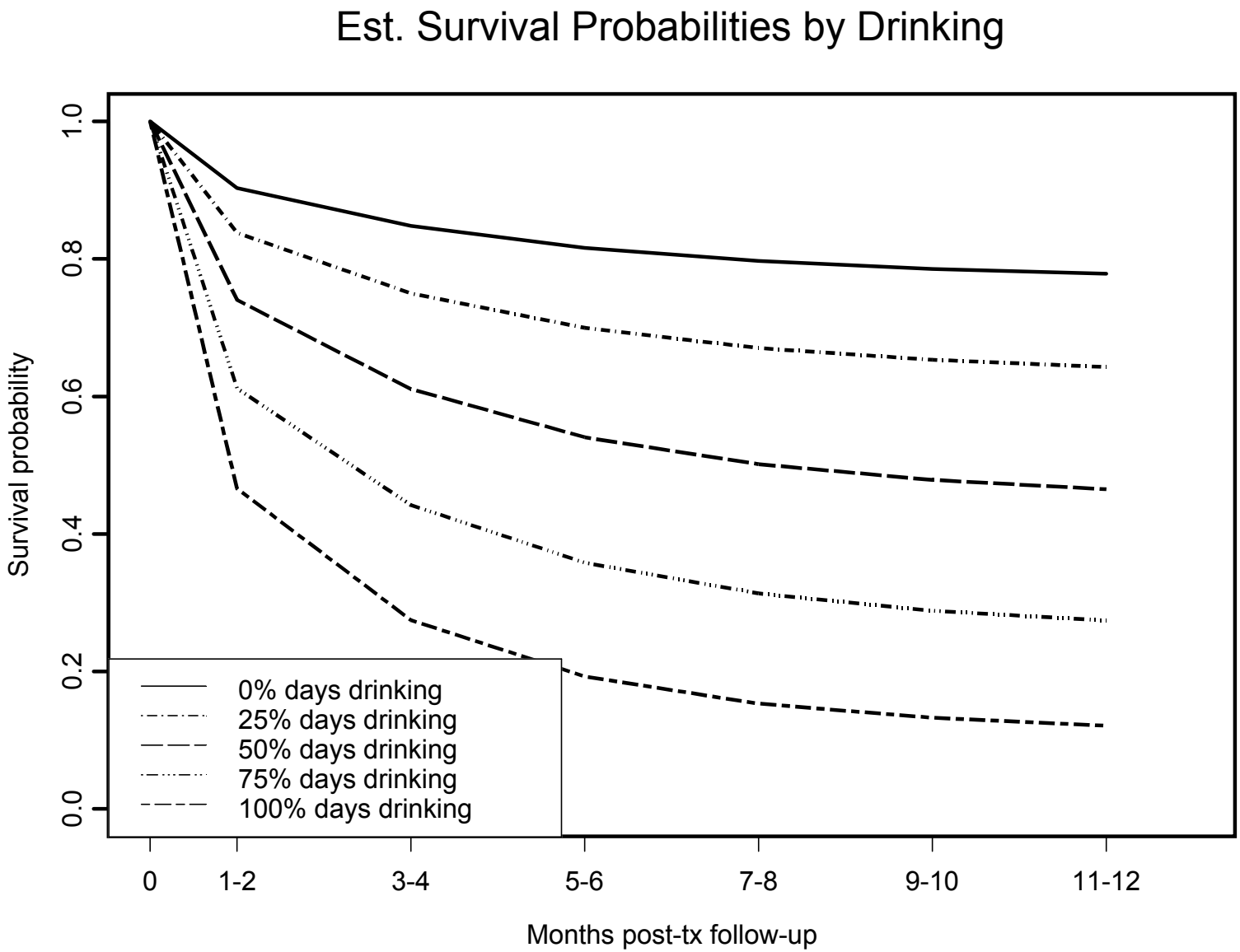
	0	*1*	*2*	*3*	*4*	*5*	*6*
$E_{R\circ_1}$		0	0	1	.	.	.
$E_{R\circ_2}$	1	.	.	.	.	.	
$E_{R\circ_3}$	0	0	1	.	.	.	
$E_{R\circ_1}$		0	0	0	1	.	.
$E_{R\circ_2}$	0	0	0	.	.	.	
$E_{R\circ_3}$	.	.	.	.	.	.	
$E_{R\circ_1}$		0	0	0	0	0	0
$E_{R\circ_2}$	.	.	.	.	.	.	
$E_{R\circ_3}$	.	.	.	.	.	.	


e11
e12
…
e1J
e20
e21
…
e2J-
z1
z2
c
z3
e30
e31
…
e3J-

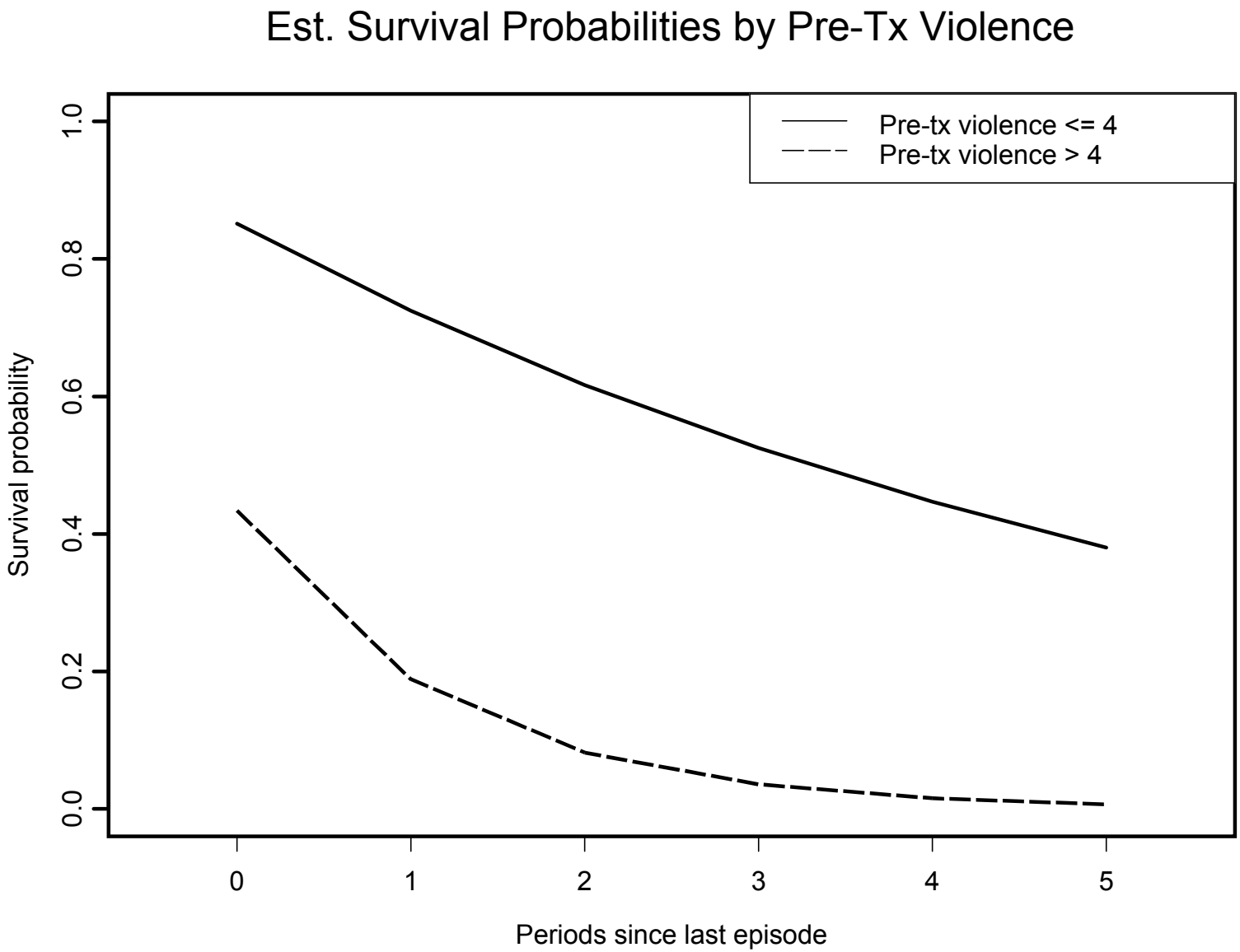
RIA example in gap time

- Violence_recur.out

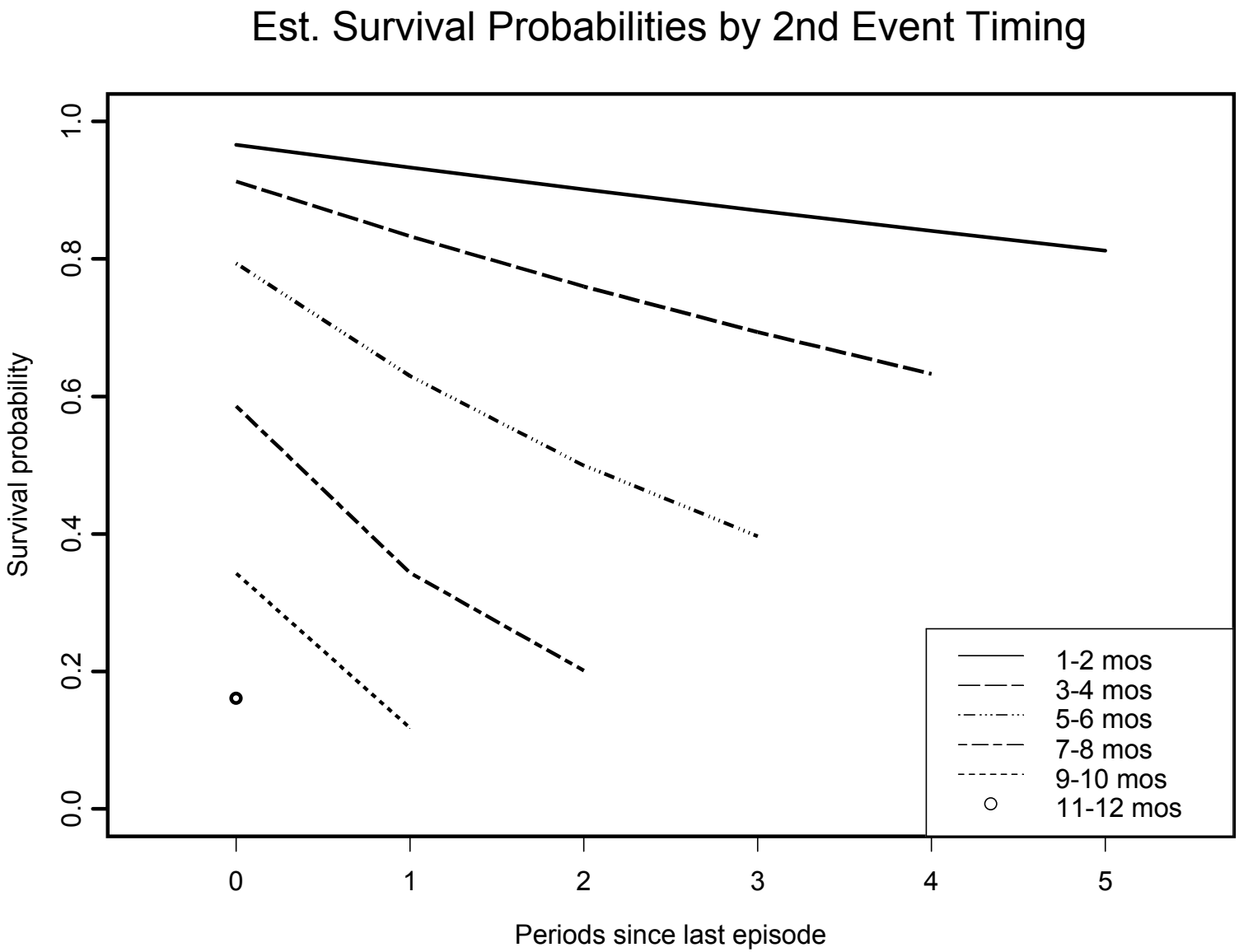
First episode by % days drinking

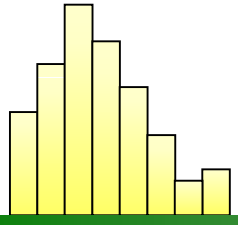


Third episode by pre-tx violence



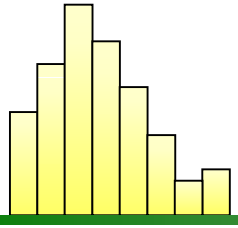
Third episode by 2nd event time





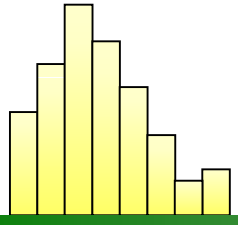
Competing risks event process features

- Individuals are at-risk for more than one event at a time provided they have not experienced any event
- Individuals cease to be at-risk for any event once at least one event has occurred
- Event times correlated within individuals
- Event-specific baseline hazard probabilities and covariate effects



Alternate conceptions of competing risks

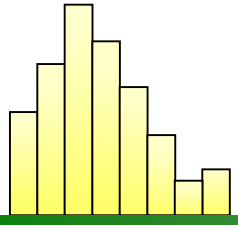
1) There are two processes at work: one that governs whether any event occurs and one that governs the type of event, conditional on the occurrence of some event.
2) There is a series of event processes (one for each event) that are running simultaneously—the occurrence of one type of event ***censors*** the other processes.



Teacher first departure from the classroom

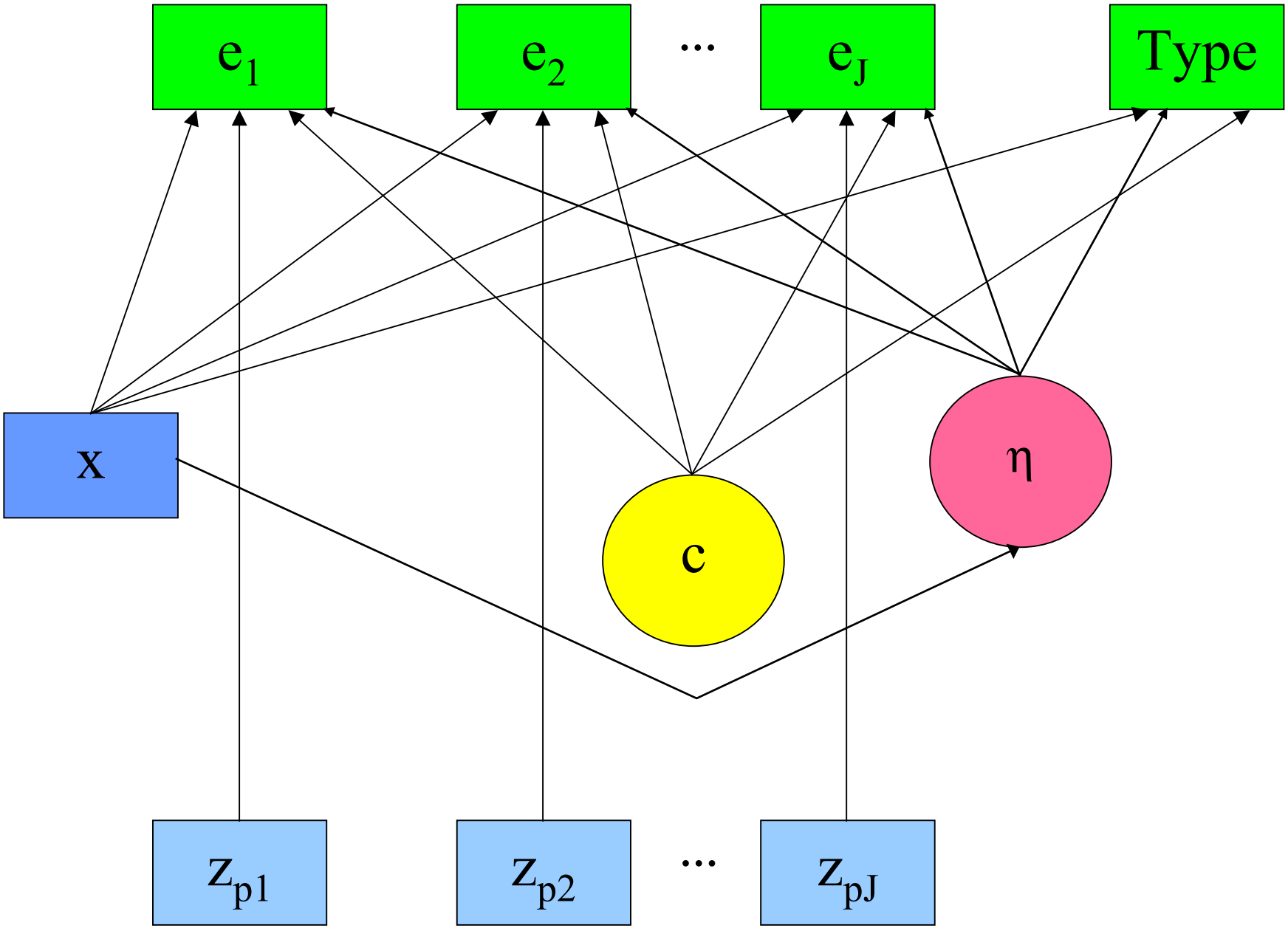
1) One processes that governs whether and when individuals leave full-time classroom teaching and one processes that governs whether, when they leave, they stay working in the field of education or not.

2) One process that governs whether and when the individuals leave full-time classroom teaching for another job in education and one process that governs whether and when the individuals leave full-time classroom teaching for another job outside education.



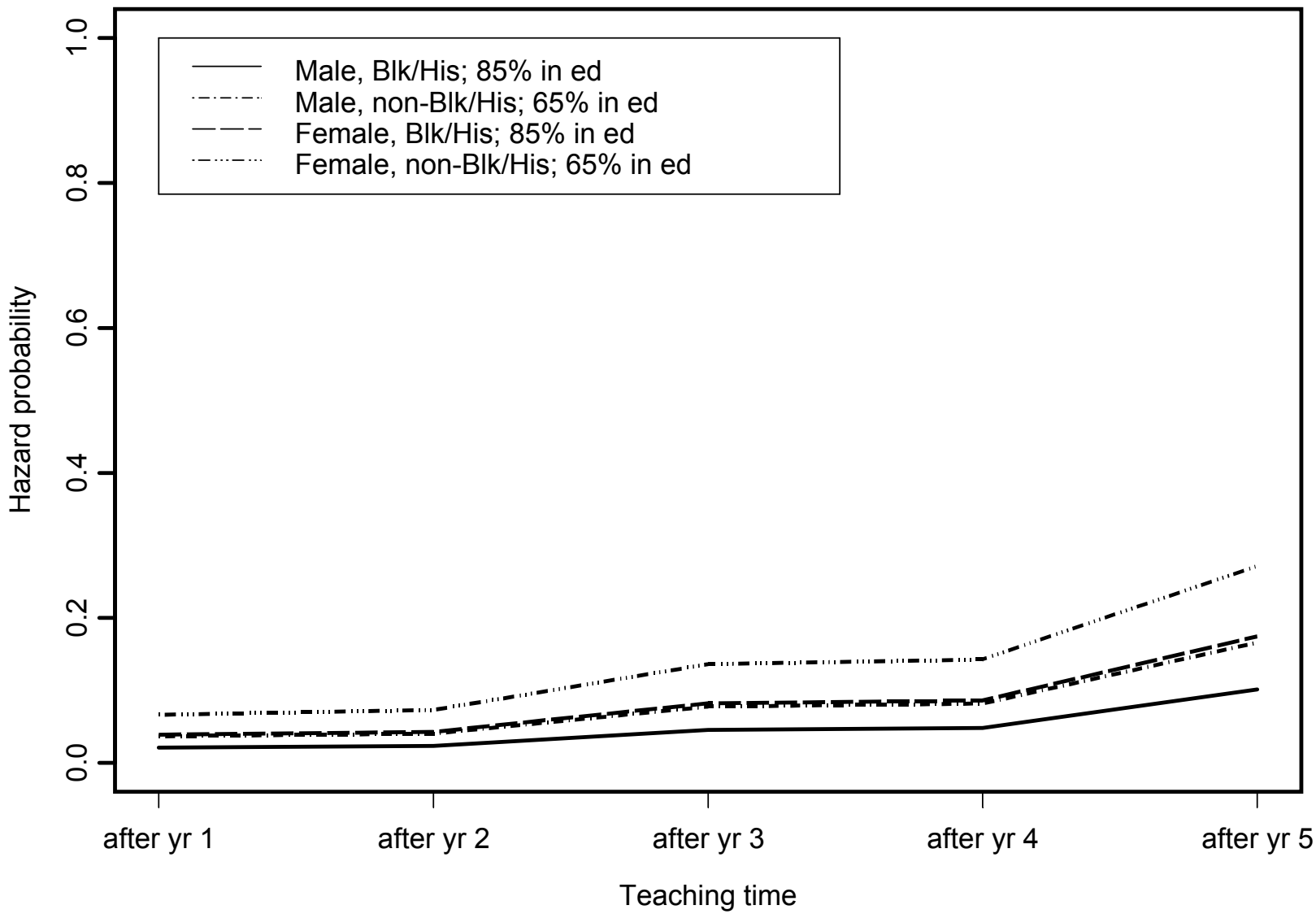
Model 1

i	e_1	e_2	e_3	e_4	e_5	*Type*
1	0	0	0	0	0	.
2	0	1	.	.	.	1
3	0	0	0	1	.	2


e1
e2
...
eJ
Type
x
η
c
zp1
zp2
...
zpJ

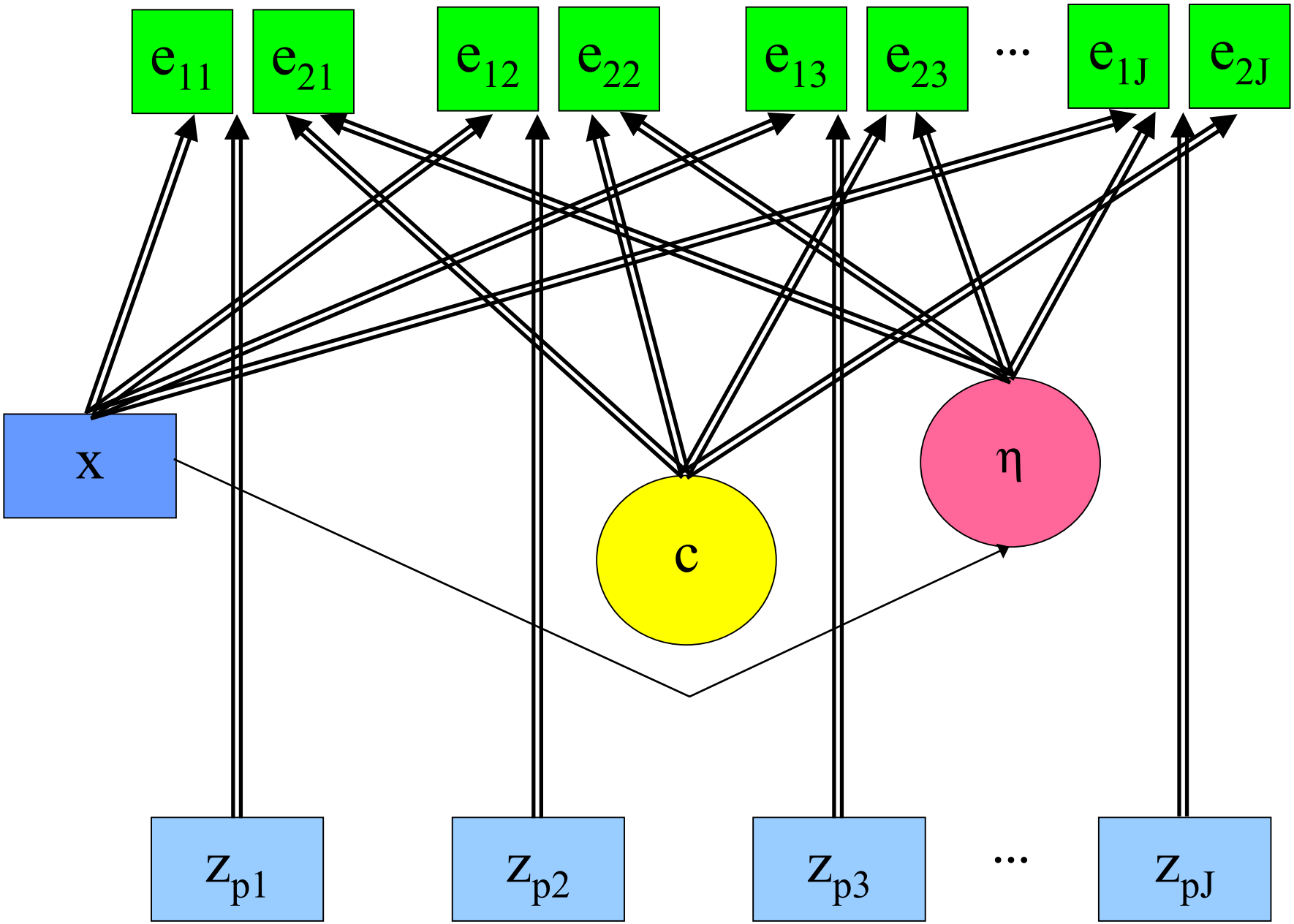
UTEC example for Model 1

- Teacher_cr_m1.out


Hazard for leaving teaching by gender and race
Male, Blk/His; 85% in ed
Male, non-Blk/His; 65% in ed
Female, Blk/His; 85% in ed
Female, non-Blk/His; 65% in ed
Hazard probability
0.0
0.2
0.4
0.6
0.8
1.0
after yr 1
after yr 2
after yr 3
after yr 4
after yr 5
Teaching time

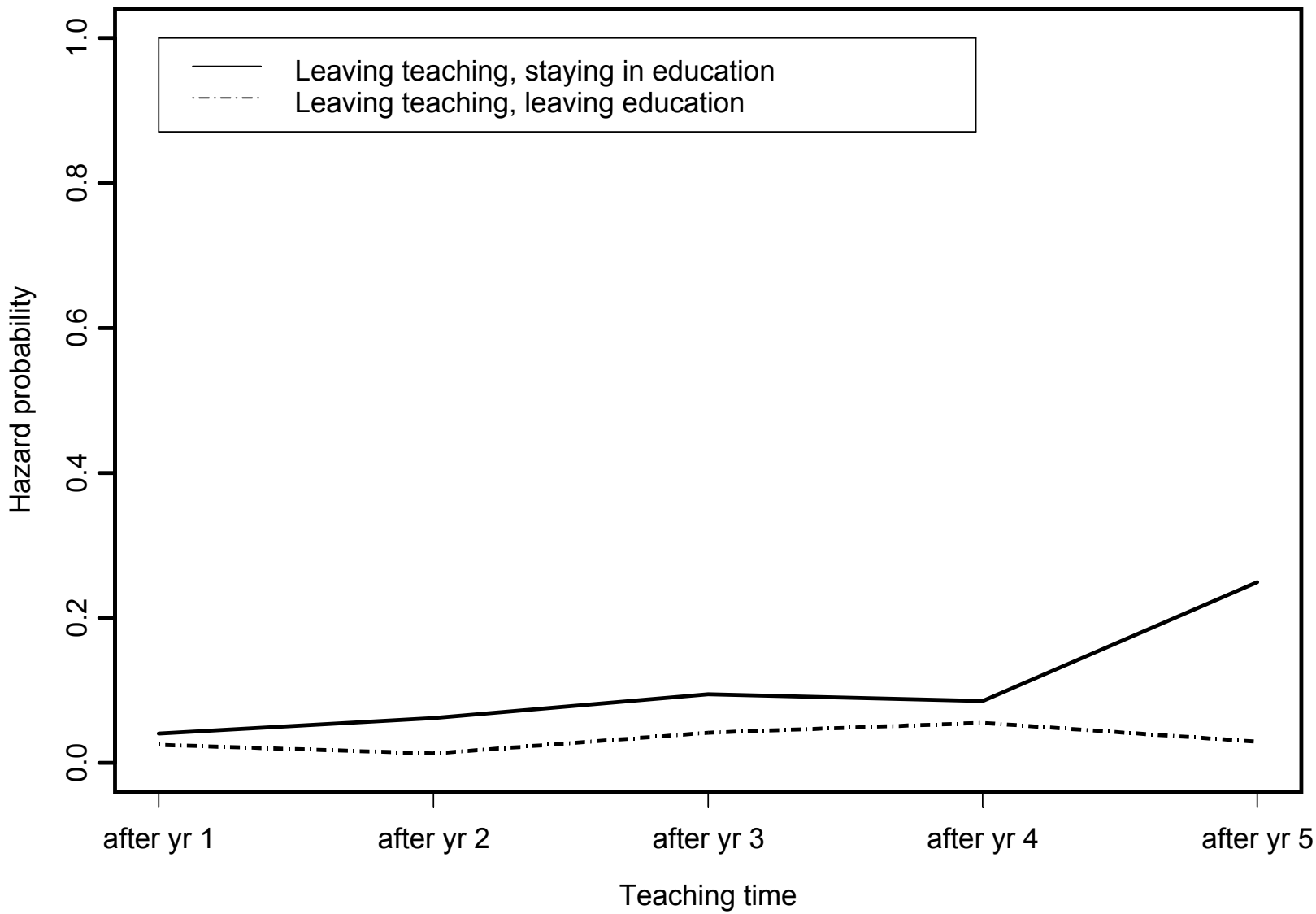
Model 2

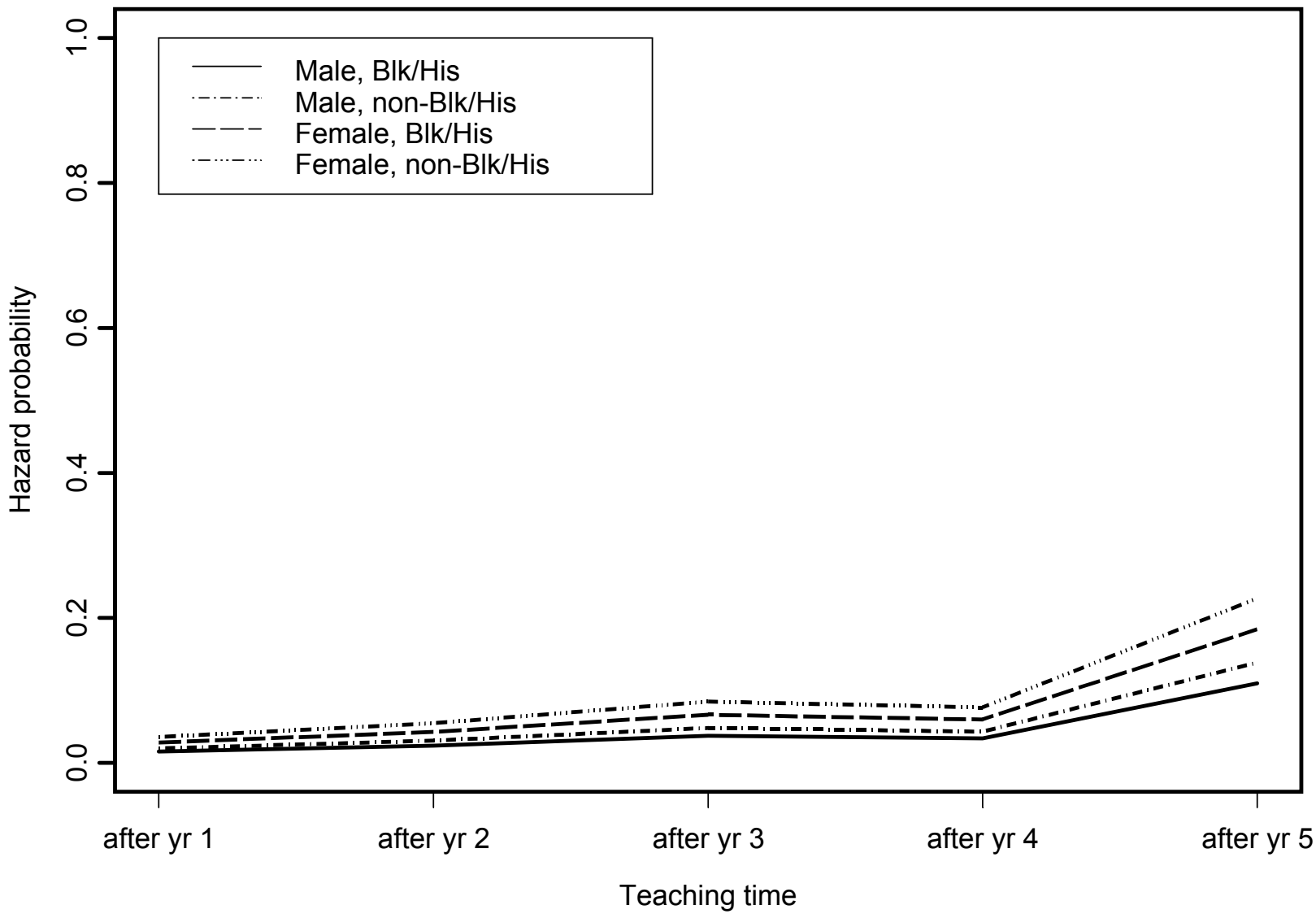
	1	*2*	*3*	*4*	*5*
$E_{R^{\circ}_{a}}$	0	0	0	0	0
$E_{R^{\circ}_{b}}$	0	0	0	0	0
$E_{R^{\circ}_{a}}$	0	1	.	.	.
$E_{R^{\circ}_{b}}$	0	0	.	.	.
$E_{R^{\circ}_{a}}$	0	0	0	0	.
$E_{R^{\circ}_{b}}$	0	0	0	1	.

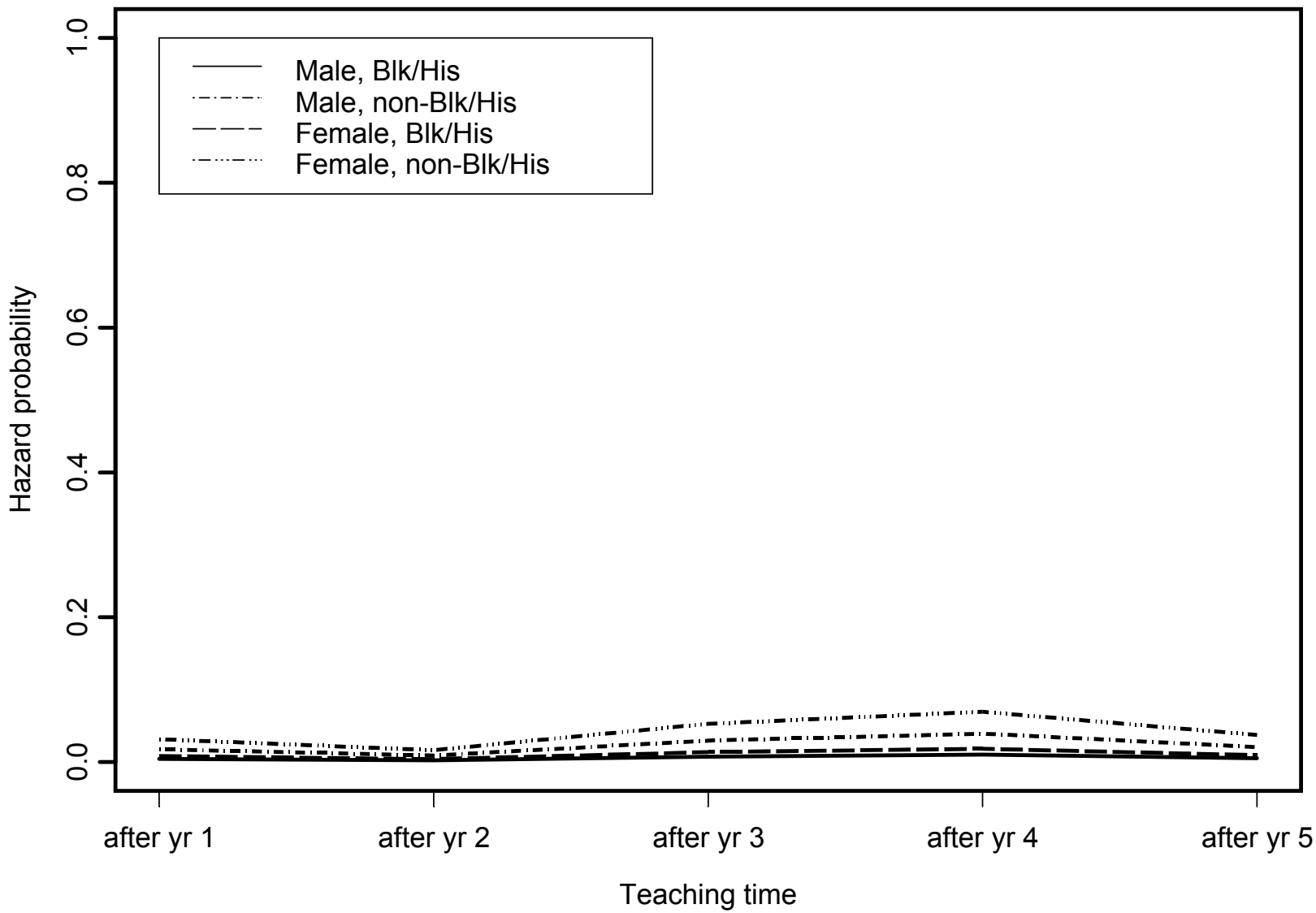

e_{11}
e_{21}
e_{12}
e_{22}
e_{13}
e_{23}
...
e_{1J}
e_{2J}
x
c
η
z_{p1}
z_{p2}
z_{p3}
...
z_{pJ}

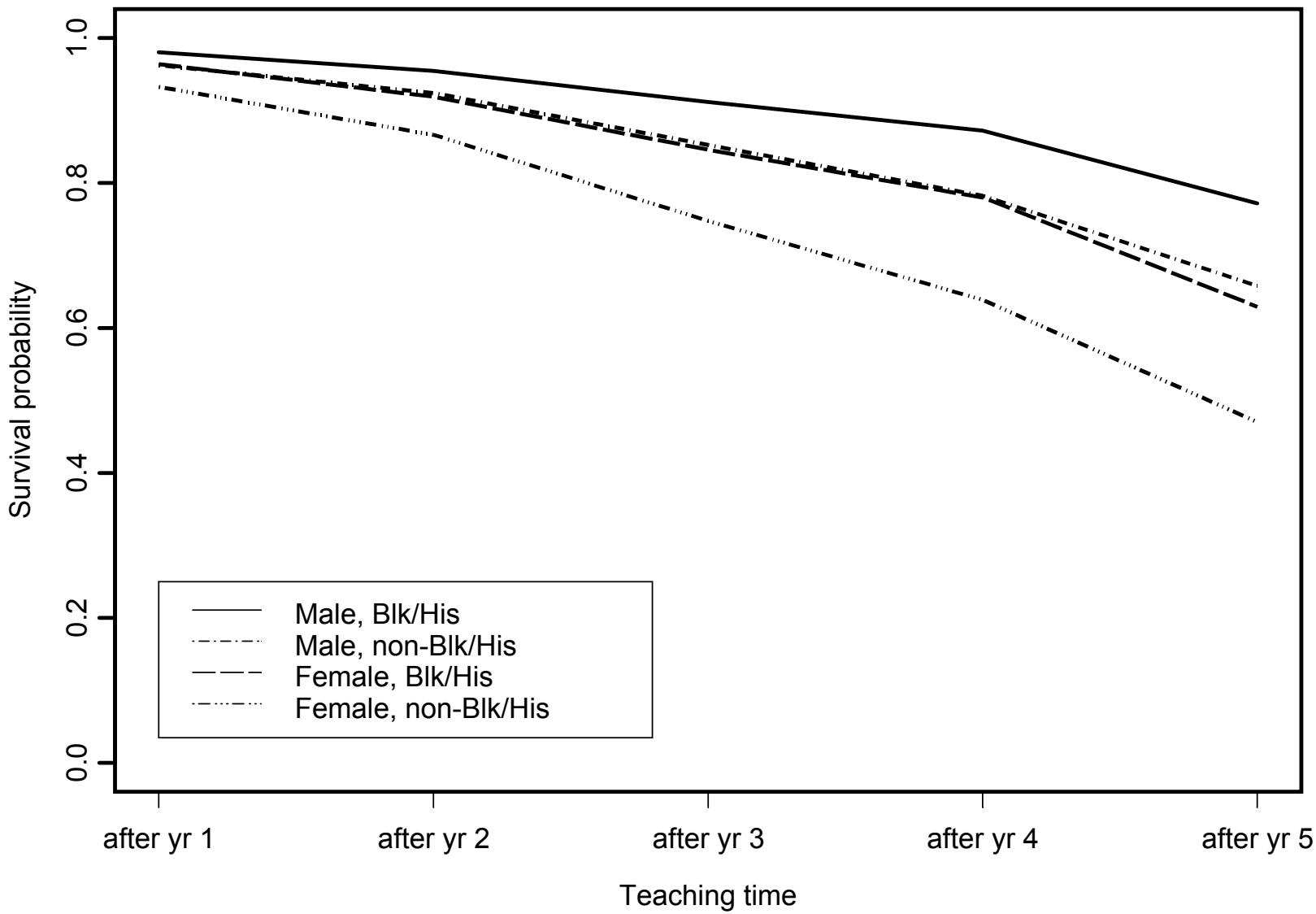
UTEC example for Model 2

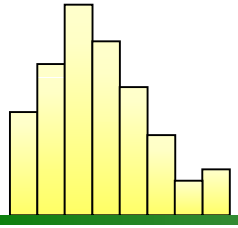
- Teacher_cr_m2.out


Hazards for leaving teaching
Leaving teaching, staying in education
Leaving teaching, leaving education
Hazard probability
0.0
0.2
0.4
0.6
0.8
1.0
after yr 1
after yr 2
after yr 3
after yr 4
after yr 5
Teaching time


Hazard for leaving teaching, staying in education
Male, Blk/His
Male, non-Blk/His
Female, Blk/His
Female, non-Blk/His
Hazard probability
0.0
0.2
0.4
0.6
0.8
1.0
after yr 1
after yr 2
after yr 3
after yr 4
after yr 5
Teaching time

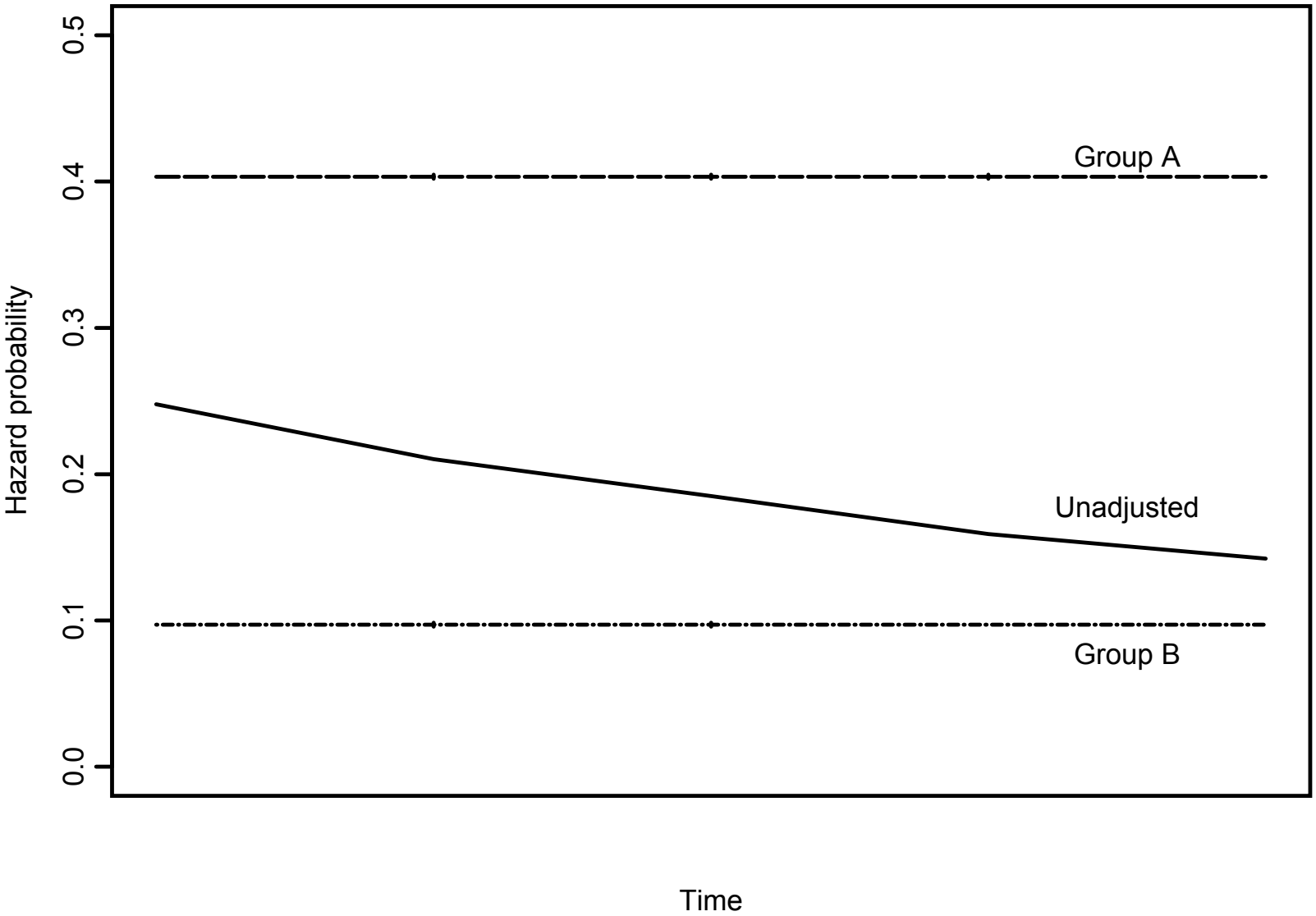

Hazard for leaving teaching, leaving education
Male, Blk/His
Male, non-Blk/His
Female, Blk/His
Female, non-Blk/His
Hazard probability
0.0
0.2
0.4
0.6
0.8
1.0
after yr 1
after yr 2
after yr 3
after yr 4
after yr 5
Teaching time

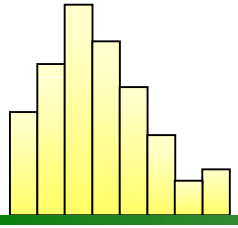

Survival for full-time teaching by gender and race
Survival probability
1.0
0.8
0.6
0.4
0.2
0.0
Male, Blk/His
Male, non-Blk/His
Female, Blk/His
Female, non-Blk/His
after yr 1
after yr 2
after yr 3
after yr 4
after yr 5
Teaching time



Unobserved heterogeneity

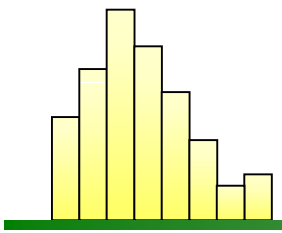
Often referred to as *frailty* in the continuous-time survival literature, this involves the idea that there may be variability in individuals' underlying (baseline) risk for an event that is not directly measurable, i.e., some individuals are more "prone" to an event than others.


Hazard probability
0.0
0.1
0.2
0.3
0.4
0.5
Group A
Unadjusted
Group B
Time



Ignoring unobserved heterogeneity

- Baseline hazard probabilities biased downward
- Time-independent covariate effects underestimated
- Spurious time-dependent effects for observed variables

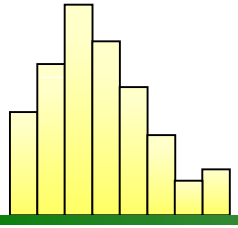


Issues in modeling unobserved heterogeneity

$$\text{logit}\, h_i(j) = -\tau_j + \beta_j x_i + \kappa_j z_{ij} + \varepsilon_i$$

- Identification
- Model specification
- Sensitivity to parametric misspecification*
- Goodness-of-fit

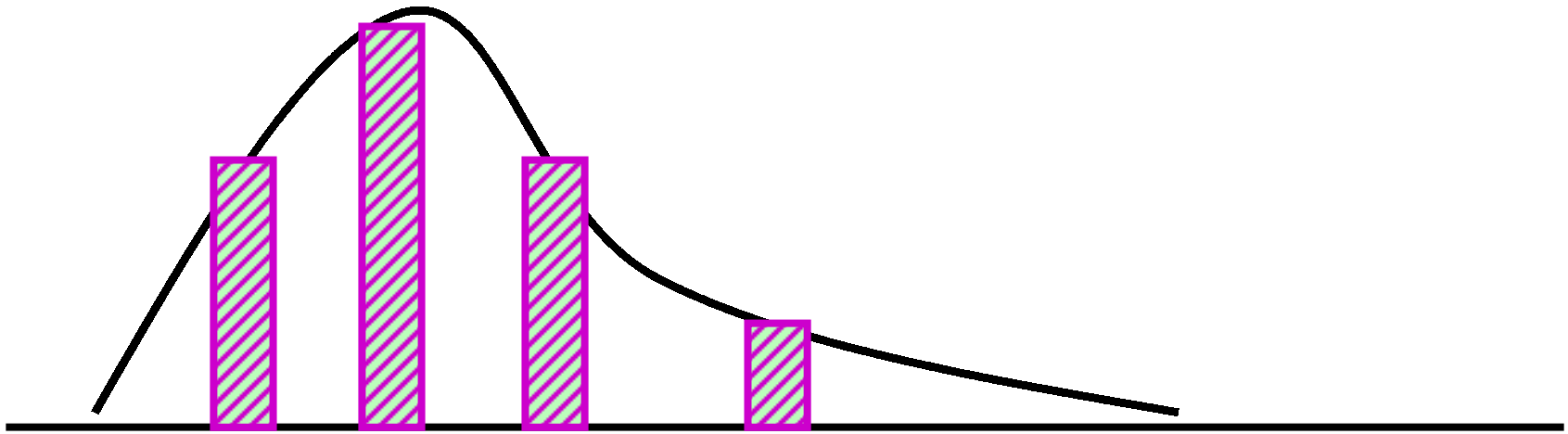
*Not as much of an issue for discrete-time as for continuous-time

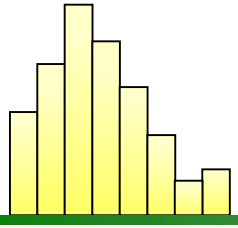


Approaches to modeling unobserved heterogeneity

- Parametric: Assume some underlying parametric distribution for ε and maximize the likelihood (requires numerical integration—now available in Version 3 for Normal distribution).

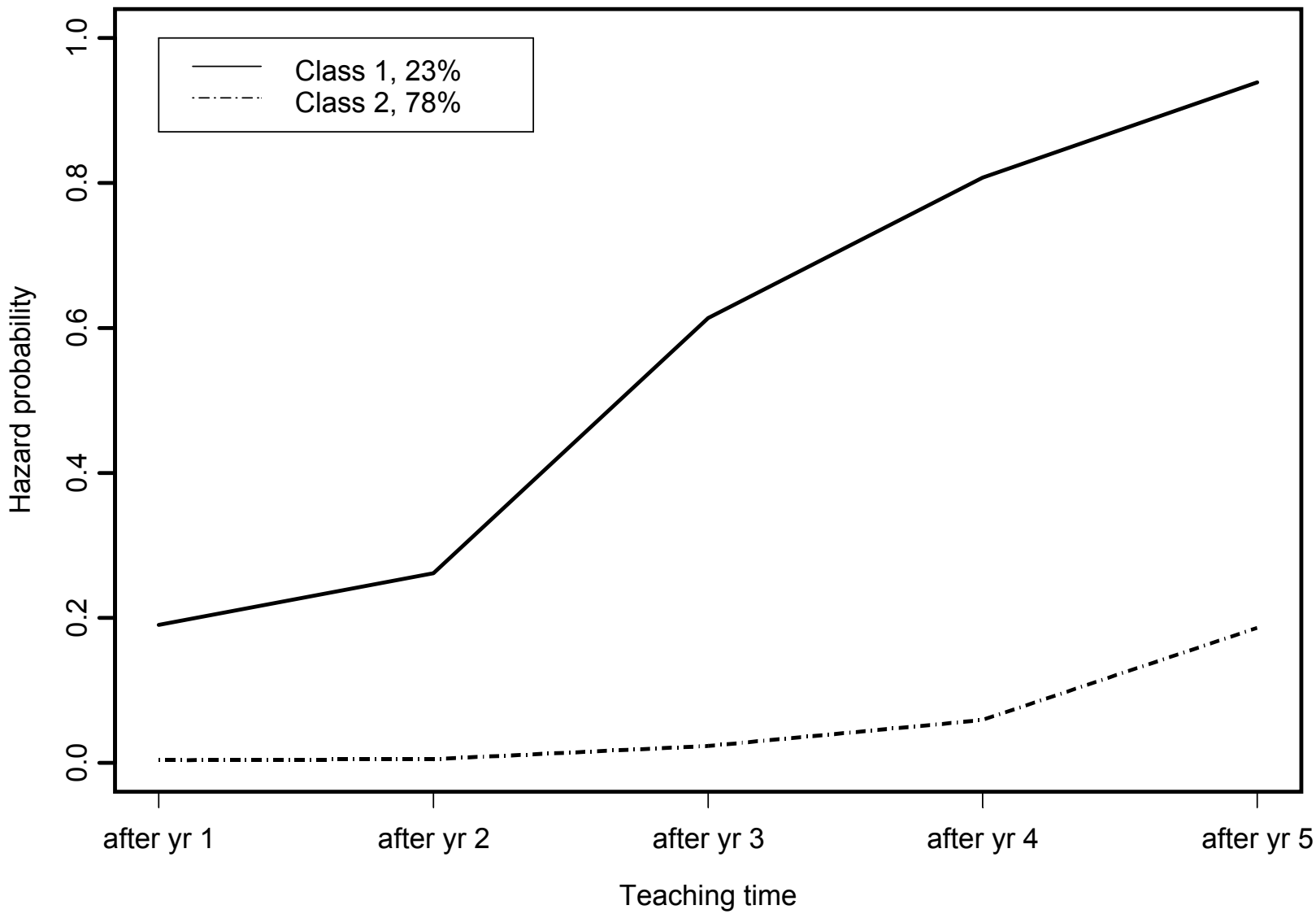
- Nonparametric: Use a finite mixture model, i.e., latent classes, to nonparametrically approximate the distribution of ε.

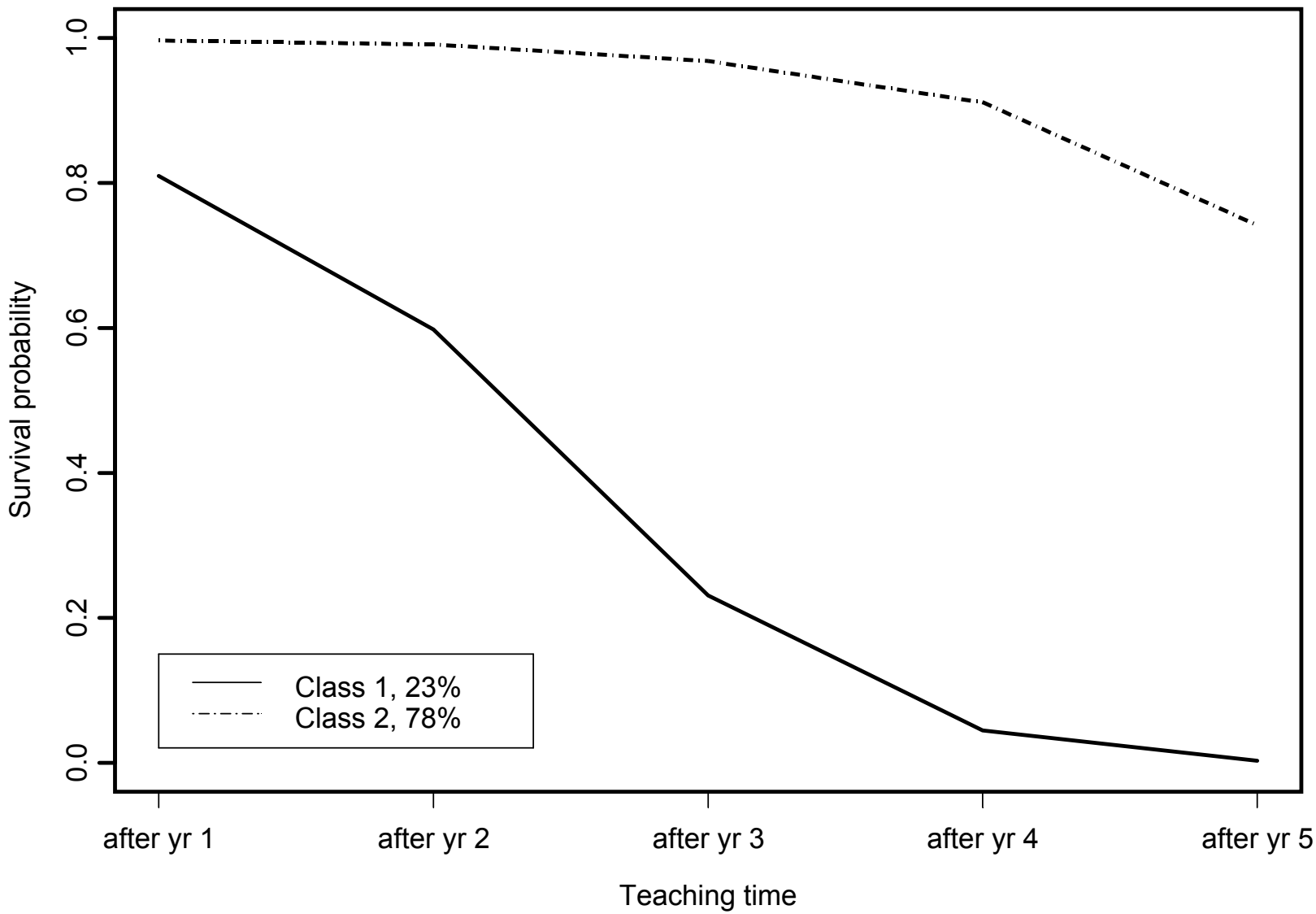


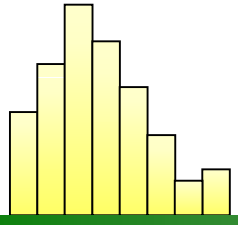


Examples w/ frailty

- Teacher_re.out
- Teacher_2c.out

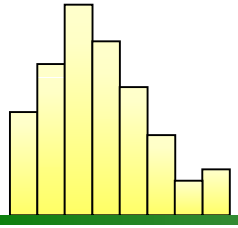

Class 1, 23%
Class 2, 78%
Hazard probability
0.0
0.2
0.4
0.6
0.8
1.0
after yr 1
after yr 2
after yr 3
after yr 4
after yr 5
Teaching time


2-class survival for full-time teaching
Survival probability
1.0
0.8
0.6
0.4
0.2
0.0
Class 1, 23%
Class 2, 78%
after yr 1
after yr 2
after yr 3
after yr 4
after yr 5
Teaching time



Multivariate event models

- The methods for incorporating individual variability or frailty in the single event models can also be used to account for event times correlated within individual in multivariate models.
- Alternatively, it is possible to reformulate these models as multilevel models with event times nested within individuals.



Extensions

- Continuous latent variable predictor of survival measured by other manifest variables, e.g., multiple survey items as measures of stress predicting time-to-event.
- Categorical latent variable predictor of survival measured by other manifest variables, e.g., clinical diagnostic criteria as measures of psychological profiles predicting time-to-event.

- Adjacent event processes
- Adjacent event and growth processes: event process followed by growth process; growth process followed by event process
- Concurrent survival processes
- Concurrent survival and growth processes