Black-White Differences in ALE in the US and the Role of SES: Illustration of a Bayesian Approach to Assessing the Importance of Intervening Variables in MSLTs

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Introduction

- Most research on ALE:
  - Uses disaggregated raw data to examine group differences in ALE
  - Generates point estimates for ALE, DLE, and TLE
  - (exception: IMaCh users)

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- But, disaggregation & point estimation has limitations
  - Does not allow statistical testing of group differences
  - More importantly, because covariates can't be modeled, it cannot allow estimation of role of intervening variables

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- In this research:
  - We show how a Bayesian approach can remedy these shortcomings
  - We do so in assessing the role of education in explaining black-white differences in ALE in the US
  - Purpose both methodological and substantive

Substantive Background

- Extant literature has studied race differences in US health and mortality extensively
  - Known that blacks fare worse until possibly in very late life: worse health, mortality rates, and ALE
  - SES differences account for a large proportion (but not majority) of differences

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- Little research has examined role of education in *ALE* differences
  - But important because ALE combines health and mortality experience
  - Important for additional reasons: cohort change in educational attainment can help us understand future of race differences in ALE

Questions:

- Are there race differences in ALE, DLE, and TLE (and the proportion ALE/TLE)
- What proportion of these racial differences are explained by education?

Data

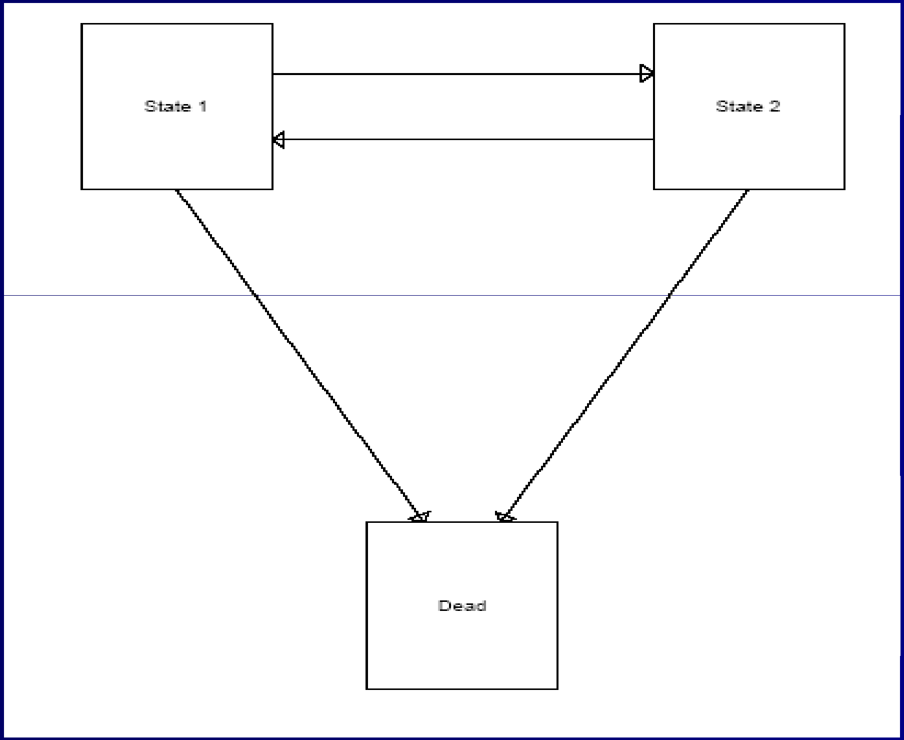
- Data from the 1987 and 1992 follow-ups to the NHANES (NHEFS)
- Limit to black and white survivors age 65+ in 1987, for whom status in ’87 and ’92 were known (n=3,056)
- Include sex, race, and education as covariates, along with age (in 5-year groups) & disability status (1+ ADLs)

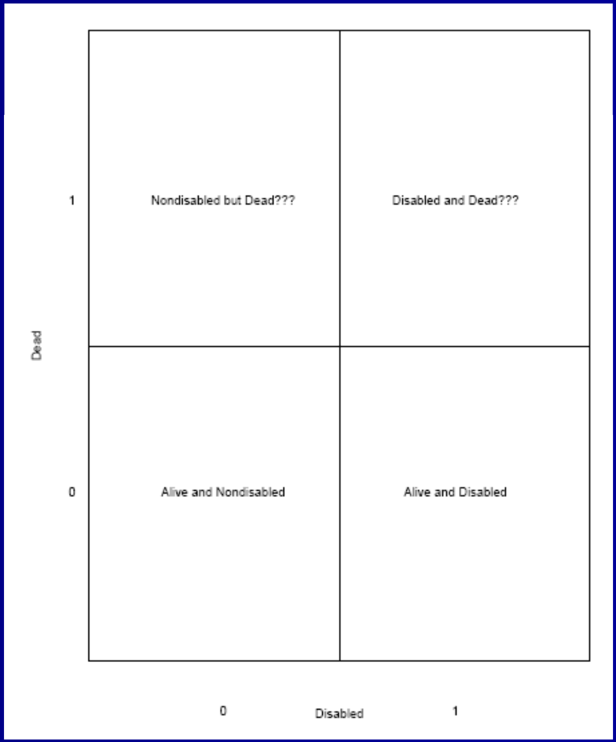
Analysis

- 1. Estimate a multivariate hazard model w/ Gibbs sampling—get *m* samples of parameters
- 2. Take distributions of parameters and generate *m* transition probability matrices for multistate life table estimation for given covariate profiles
- 3. Summarize distributions of ALE

Analysis, cont'd

- State space for model is:





Model Estimation

- Use Gibbs sampling
  - Simulate $(Y^*, Z^* \mid \beta, \omega, \Sigma) \sim TBvn()$ (bivariate normal latent data for observed bivariate dichotomous data)
  - Simulate $(\beta_j \mid \beta_{-j}, \omega, \Sigma, Y^*, Z^*) \sim N()$
  - Simulate $(\Sigma \mid \beta, \omega, Y^*, Z^*) \sim InvW()$
  - Repeat

Life Table Estimation

- Tables are estimated for each parameter sample from the Gibbs sampler
  - Choose covariate profile and construct transition probability matrices
  - Generate mslts using a basic approach:

$$l(i, a+1) = l(i, a) + l(+i, a) - l(-i, a)$$

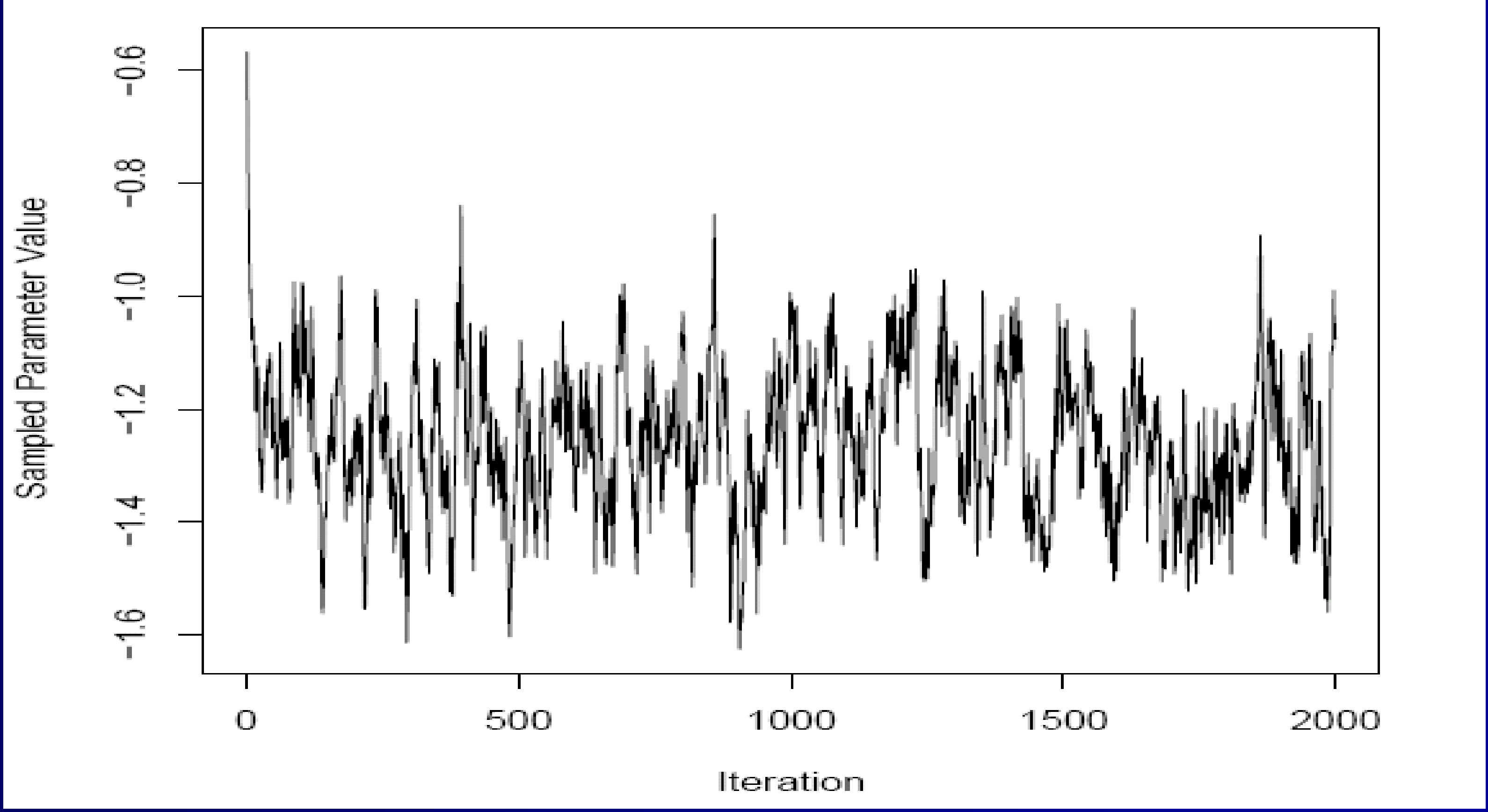
Issues: How account for race differences?

- Choice of hazard model(s)
  - One model with education included
- Choice of covariate profiles
  - Set female=.5
  - Four profiles: black/white; black/white means for education
- Choice of radices
  - Two sets: black/white proportions at 65

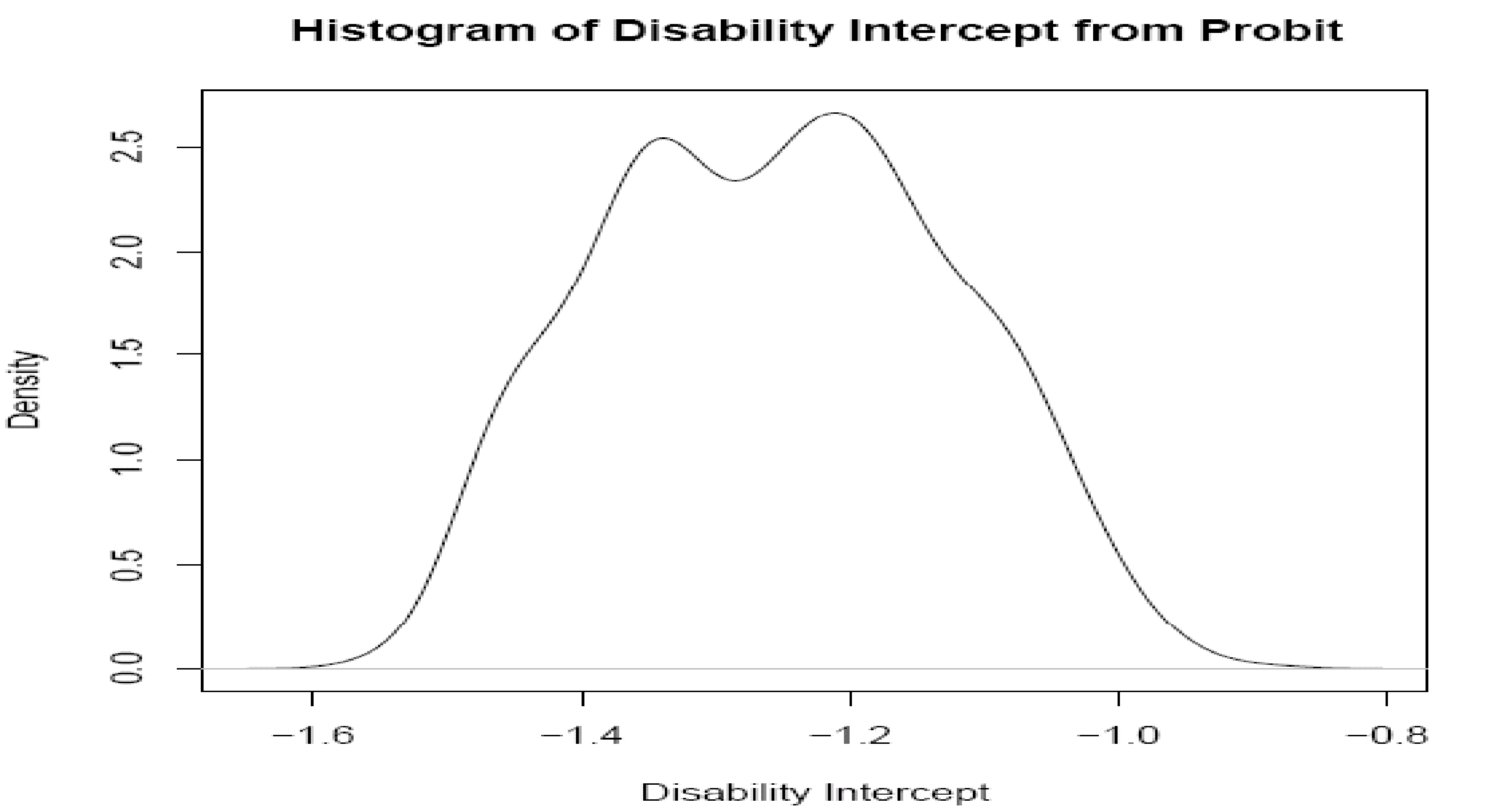
Descriptives

Variable	B (n=355)	W (n=2701)
Age	MD~77	MD~76
Female	65.1%	60.9%
Education	7.9(3.9)	10.5(3.4)
Start Disabled	25.1%	16.4%
End Disabled	20.8/32.0%	14.8/21.4%
End Dead	34.9%	30.9%

Gibbs Trace Plot, e.g.



Histogram of (Disability) Intercept from Gibbs Sampler



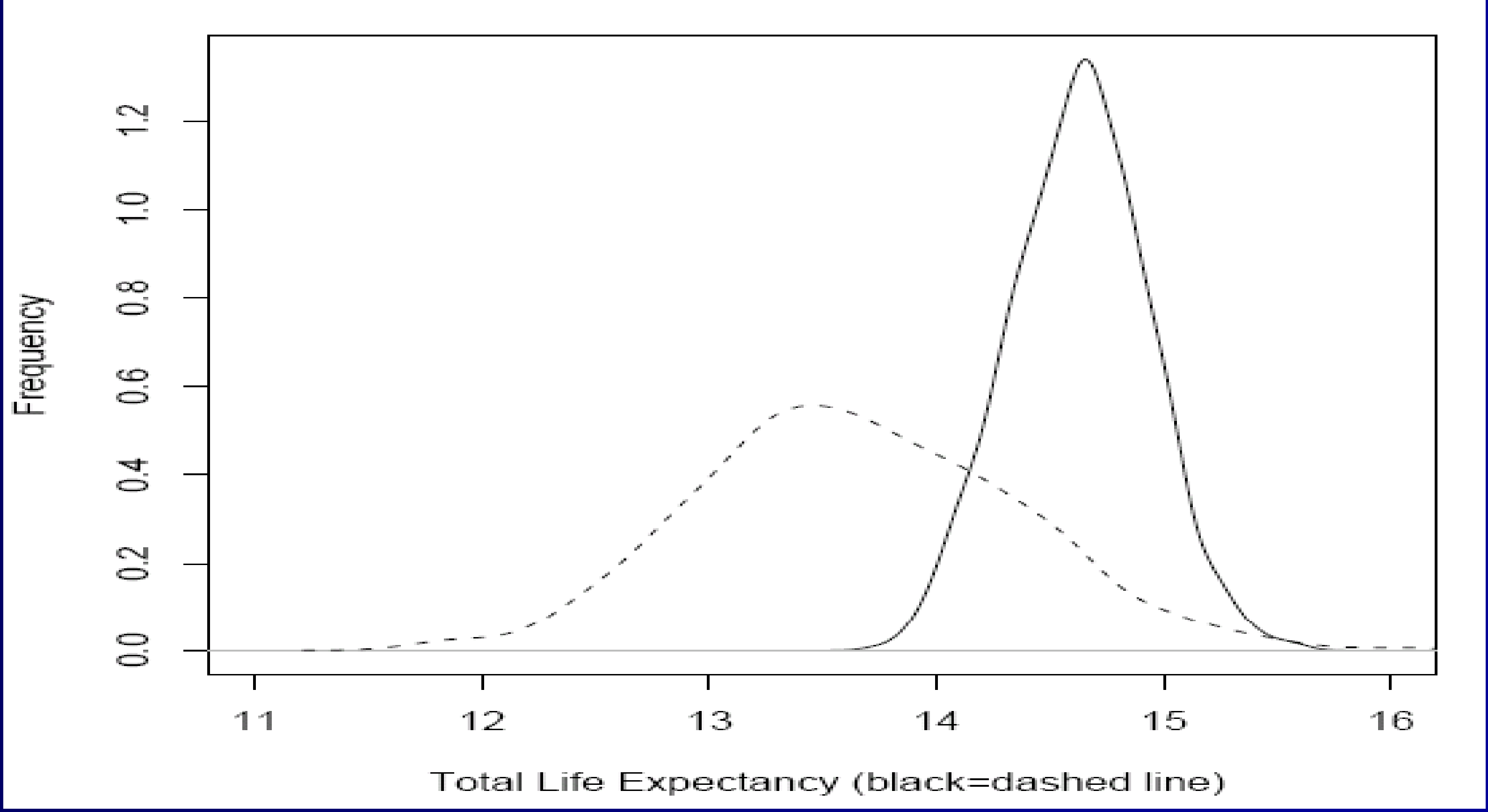
Probit Results

Variable	Dis.	Death	Dis.	Death
Const.	-1.4***	-1.1***	-1.3***	-.8***
Age	.22***	.32***	.22***	.33***
Dt1	1.55***	.69***	1.6***	.64***
A*Dt1	-.20***	0	-.21***	.01
Female	.10**	-.40***	.10	-.39***
Black	**.21***	**.03**	**.18#**	**-.02**
Educ.			**-.01**	**-.02***

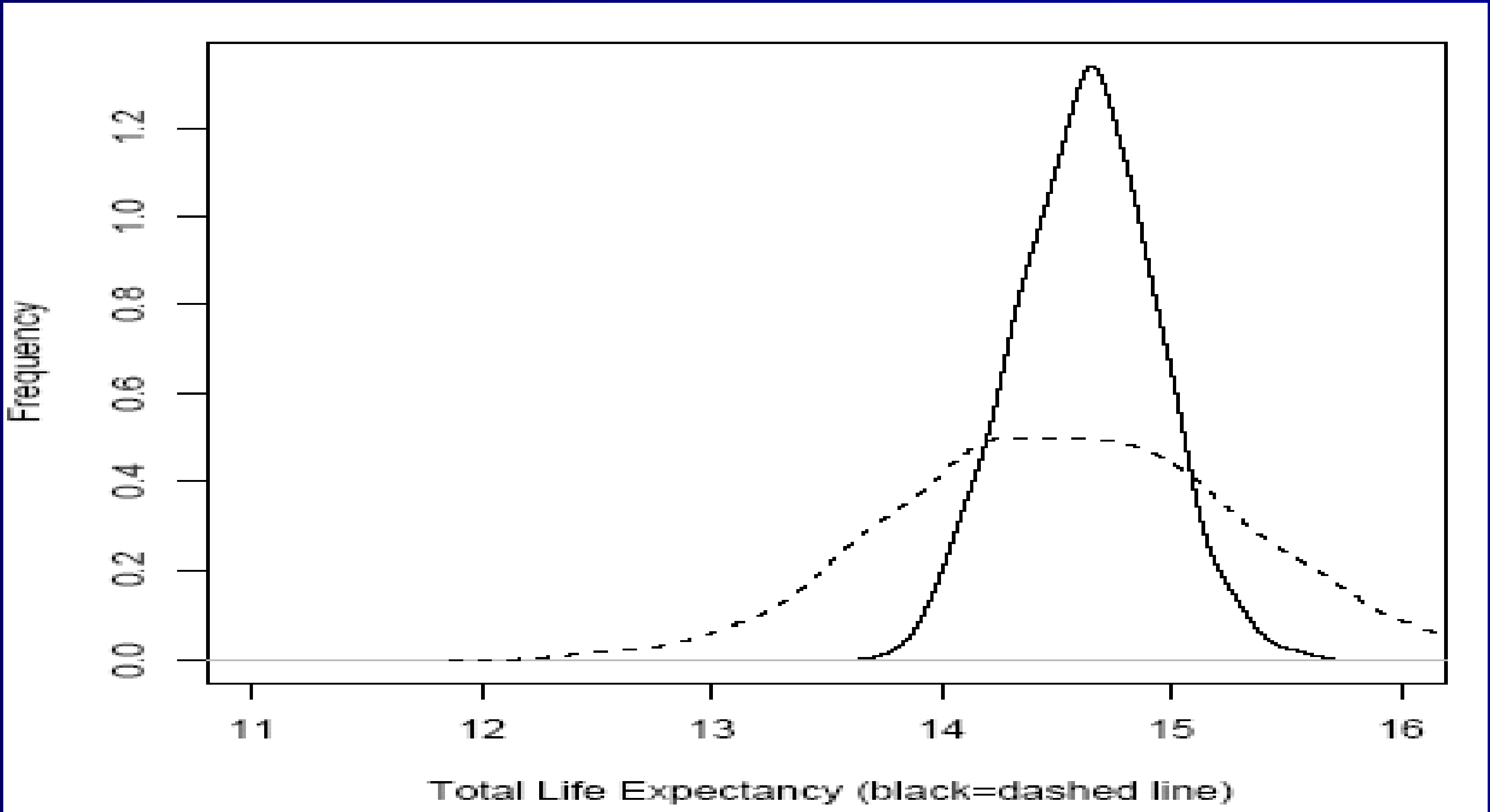
Interpretation of Probit

- If just using standard interpretation, education "explains" 14.3% of difference in disability between blacks and whites
- Similarly, education "explains" (*more than*) 100% of mortality difference
- But, what about ALE (and TLE)?

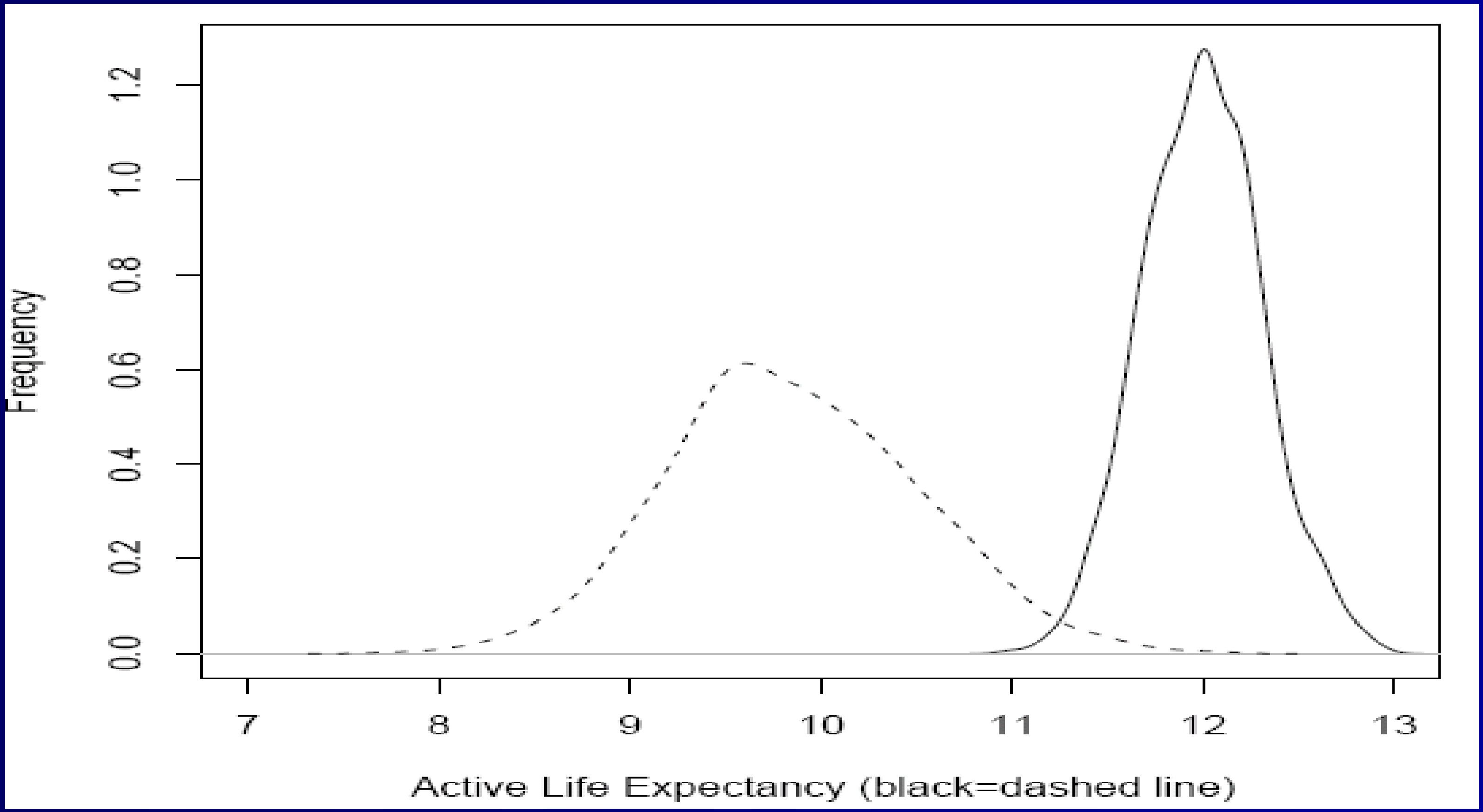
Black and White TLE: Education *not* Controlled



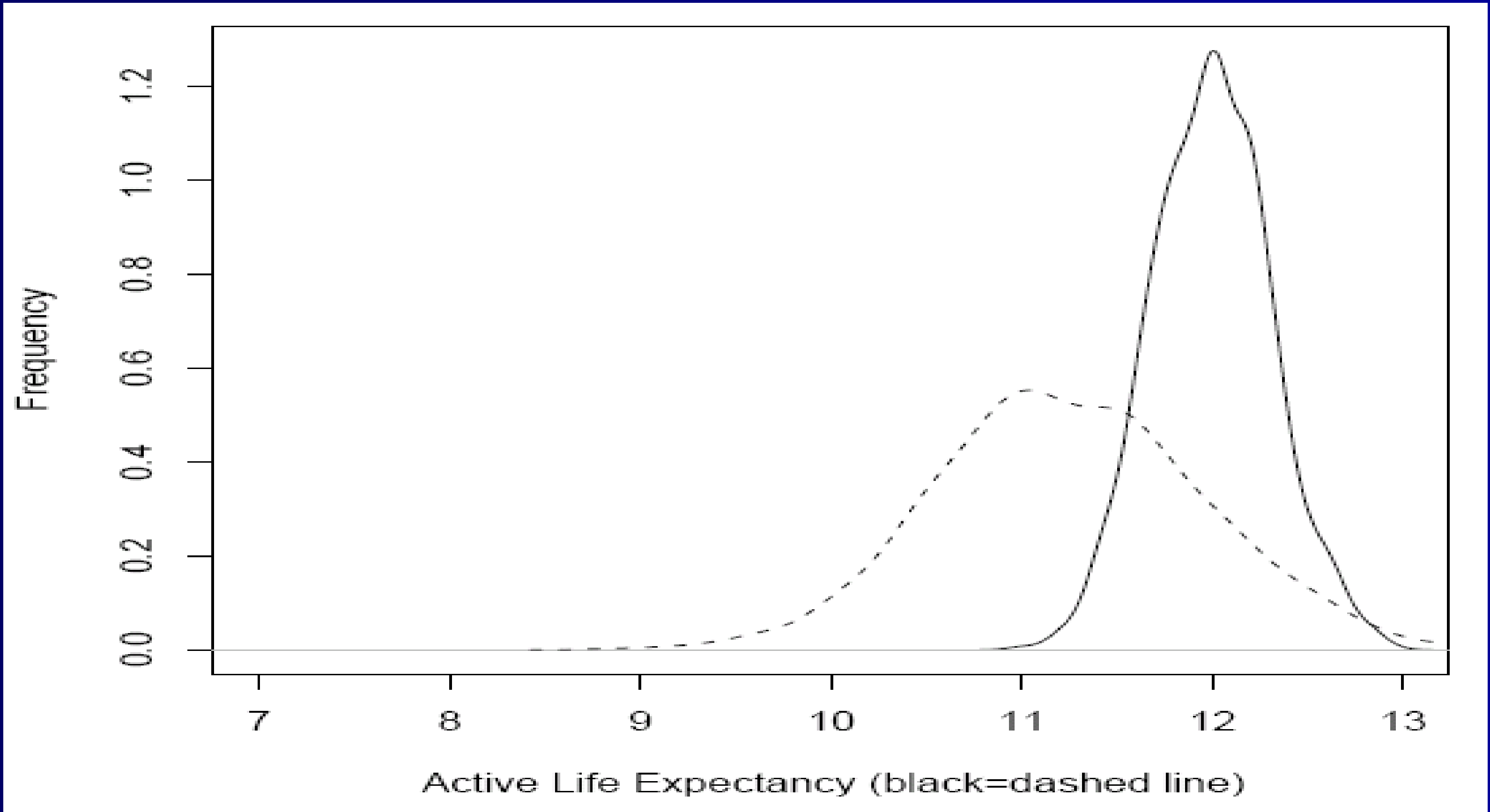
Black and White TLE: Education Controlled



Black and White ALE: Education *not* Controlled



Black and White ALE: Education Controlled



Change in ALE and TLE with Inclusion of Education

Cov. Profile	White (ALE/TLE)	Black	Chg(%)
BR-BM	*12.0(.31)*	9.86(.7)	2.13
	14.6(.30)	13.7(.7)	.97
WR-BM	*12.0(.31)*	10.88(.7)	1.11(48%)
	14.6(.30)	14.12(.7)	.51(47%)
WR-WM	*12.0(.31)*	11.3(.7)	.74 (65% / 34%)
	14.6(.30)	14.6(.8)	.07 (97% / 86%)

Substantive Conclusions

- Not substantial race differences at 65 in TLE, *but*
- Significant differences in ALE and ALE/TLE exist
- If radices are *not a function of education*, 34% of ALE difference is explained by education differences; 86% of TLE is
- If radices *are* a (total) function of education, 65% of ALE difference is explained by education differences; 97% of TLE is

Methodological Notes

- Approach works very well and is flexible
  - Software allows unlimited covariates
  - "Always" converges with Gibbs sampling
  - Hazard model run takes about 5-10 minutes; life table construction takes about 5 minutes

Cont'd

Limitations

- Written in Unix-based C only, at the moment
- Age-dependence is probit only
- Limited to 3 states
- No random effect for multiple waves yet

Cont'd

- Questions:
  - What is the best way to set radices???
  - How can cohort change be considered???
  - Proportional change in ALE (to TLE) only changes by 5%: how should this be interpreted?

Full Conceptual Model