Heterogeneity in active life expectancy: A finite mixture model

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Two main ways to compute ALE:

(1) “Sullivan”

- Computationally simple
- Uses population-level data to compute population-level indicator
- Imposes NO assumptions about underlying disability dynamics (i.e., onset, recovery, timing)

Two main ways to compute ALE:

(2) MSLT (“event-history”)

- Computationally complex
- Uses individual-level data to compute population-level indicator
- Imposes strong (and obviously inappropriate) Markov assumption about underlying disability dynamics
- Requires “event” data (which we <u>never</u> have; there may not even BE “events”)

Both: typically ignore unobserved heterogeneity

A new approach: a discrete-mixture joint model of …

(a) disability “trajectories” (average pathways)

(b) survivorship/mortality

(c) missingness vs. completeness of panel data

This combines some of the attractive features of “Sullivan” (mainly, no assumption about disability dynamics) with attractive features of MSLT (uses individual-level panel data) while introducing

(i) mortality correlated with disability risk,

(ii) explicit treatment of unobserved heterogeneity,

(iii) a correction for informative missing data.

Data:

Sample consists of HRS respondents age 65 plus in 1998, followed biennially to 2014 (9 “waves”)

Variables:

D_1, … , D_9 = binary indicators of “gets help with ADLs”

age_1, … , “lastage” (= age_9 OR age at death)

indicator of censorship vs. observed death

R_1, … , R_9 = “retained” (a non-missingness indicator)

Model: 3-dimensional joint model of D, S, R

In each dimension we condition on latent (unobserved) class membership; there are C classes (the number of which is determined by the data)

Conditional on $c = 1, \ldots, C$:

$\Pr(D_t = 1) = \text{logit}(\beta_{0c} + \beta_{1c}\text{age}_t + \beta_{2c}\text{age}_t^2)$

survival/death at "lastage" uses Gompertz function with intercept α_c and slope λ

$\Pr(R_t = 1) = \text{logit}(\theta_c)$ (i.e., a Bernoulli process)

This is a type of "frailty" model; frailty takes the form of (unobserved) class-membership indicator (rather than as (additive) term in (log-) hazard of mortality

At "origin" age, age_0 (for us, age 65):

Pr(individual i is in class c) = $\pi_c(age_0)$

Class-membership probabilities evolve with age due to selective mortality (Vaupel and Yashin 1985):

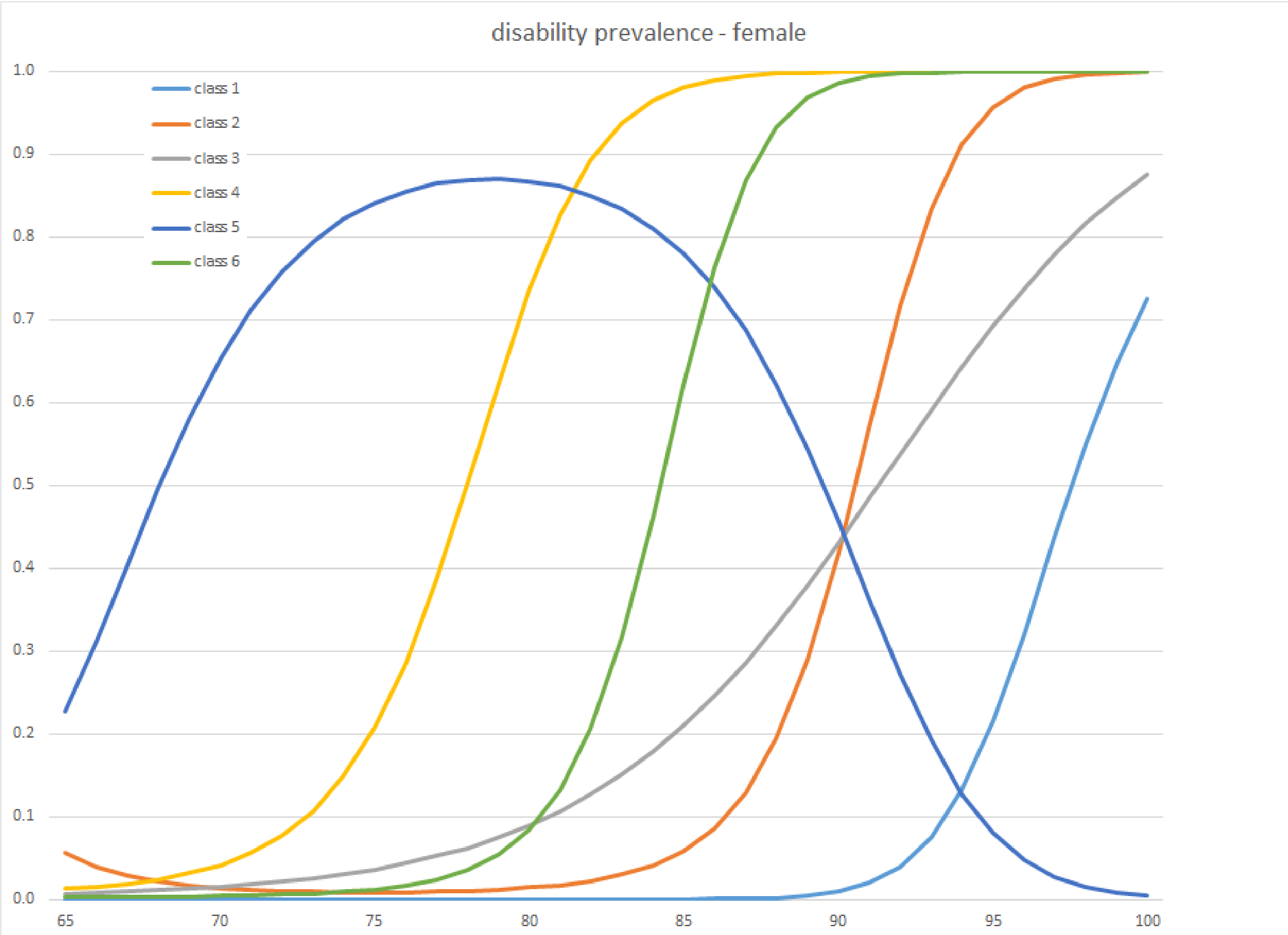
Pr(in class c AND survive to age_t) = $\pi_c(age_0)S_c(a_t)$

Pr(in class c <u>at</u> age_t) = $\pi_c(age_t) = \dfrac{\pi_c(age_0)S_c(a_t)}{\sum_{c'=1}^{C}\pi_{c'}(age_0)S_{c'}(a_t)}$

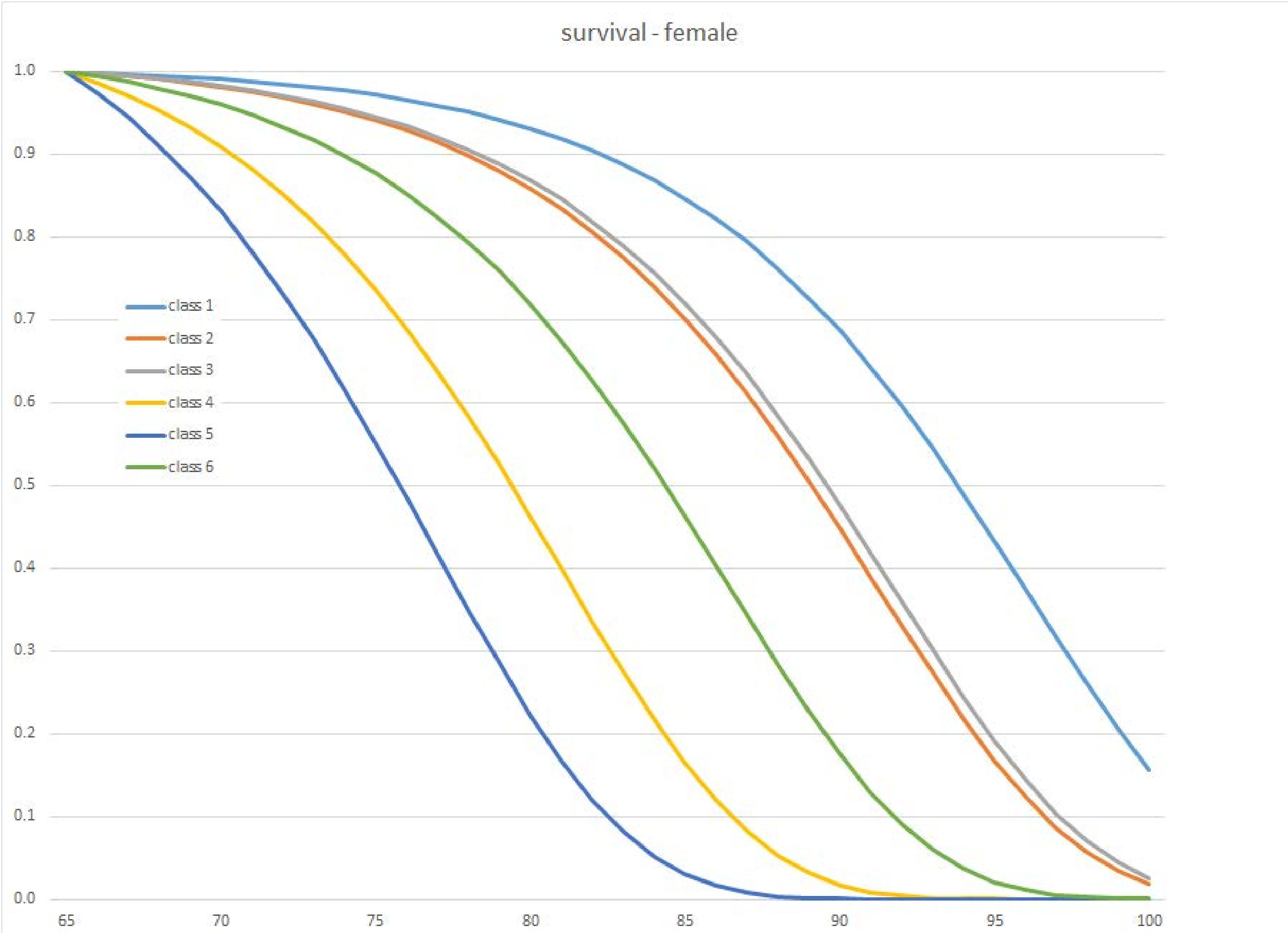
Results:

Data indicates 6 classes for women, 5 for men.

Graphical representation of disablement, women:



Graphical representation of survivorship, women:



Delayed disablement combines with <u>longer</u> survival, and early disablement combines with <u>poorer</u> survival (i.e., mortality risk and probability of having a disability are positively correlated).

Summary of results:

	class 1	class 2	class 3	class 4	class 5	class 6	Total
Women							
DLE	2.0	4.1	6.0	7.3	6.6	7.5	5.5
ALE	26.7	20.9	20.5	10.6	4.0	16.0	17.1
TLE	28.7	25.1	26.5	17.9	10.6	23.6	22.6
$\pi_{65}(c)$	14.7%	27.4%	7.0%	17.8%	10.2%	23.0%	
Men							
DLE	2.5	2.5	4.2	5.8	9.7	--	4.6
ALE	20.9	22.3	15.7	10.3	4.1	--	15.2
TLE	23.4	24.7	19.9	16.1	13.7	--	19.9
$\pi_{65}(c)$	4.3%	28.4%	33.0%	23.0%	11.2%	--	

Conclusions:

Women’s ALE > men’s ALE;

Women’s DLE > men’s DLE;

There is a LOT of heterogeneity;

For each gender, there is a modestly substantial class with very unfavorable LE: 10% of women in class where 62% of remaining lifetime spent with disability; 11% of men are in class where 71% of remaining lifetime spent with disability;

For each gender, the largest class has least- (or nearly so) disabled residual life expectancy;

Some evidence of “recovery” but relatively few survive to manifest it.

Limitations:

- Model seems to need some work (TLE 9-11% too high compared to US 2006 LT);
- Requires use of “synthetic cohort” approach (but ALL methods of calculating ALE do);
- Requires complex estimation software (but our SAS program is freely available).