Latent Health Dynamics

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2. Solving dynamic structural models is hard:
   - Even fairly basic models have computational burden
   - Adding 1 more state variable $\Longrightarrow$ curse of dimensionality
   - Adding several state variables? Things get tricky...

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  - How much adverse selection should we expect for LTDI?
  - What are the welfare implications of individually rated vs community rated health insurance premiums?
- If "health" is complex **and** adding complexity to dynamic structural models is hard... then something's gotta give!

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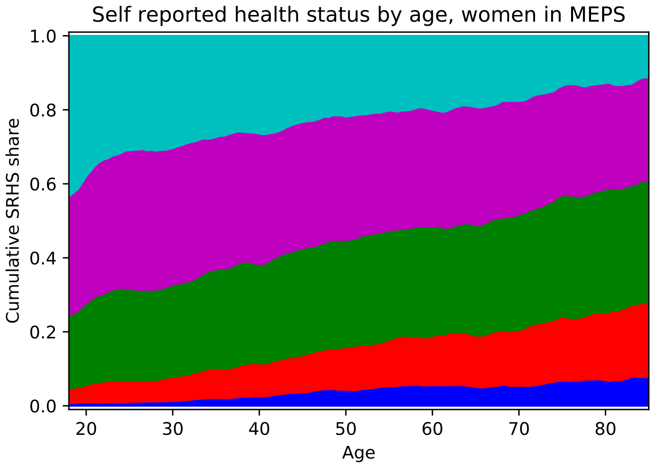
- **BHPS**: "Compared to people of your own age, would you say that your health has on the whole been... Excellent, Goode, Faire, Poore, Very Poore"

SRHS by age in MEPS (women)



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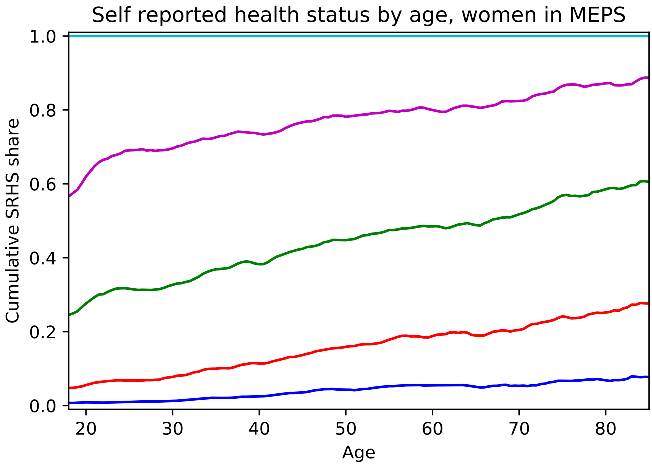

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  - Labor supply (Bound (1991), Blundell et al (2017))
- **And** it's highly correlated with objective clinical measures that directly measure aspects of "health" (LaRue (1979))
- Cheap and easy to survey, everyone understands the question, correlated with the thing we want to measure, predictive of relevant outcomes, simple to implement in models...
- ...So what's the problem?

Standard implementation of SRHS

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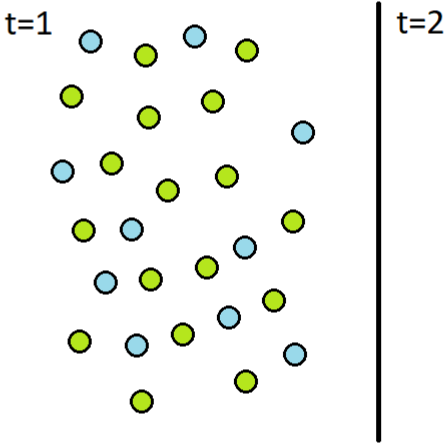
- And taking SRHS **way** too literally

Taking SRHS transitions "straight from the data"



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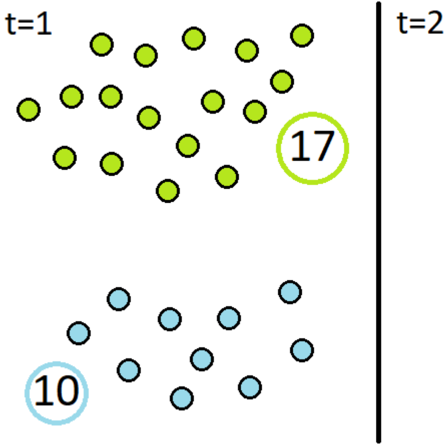

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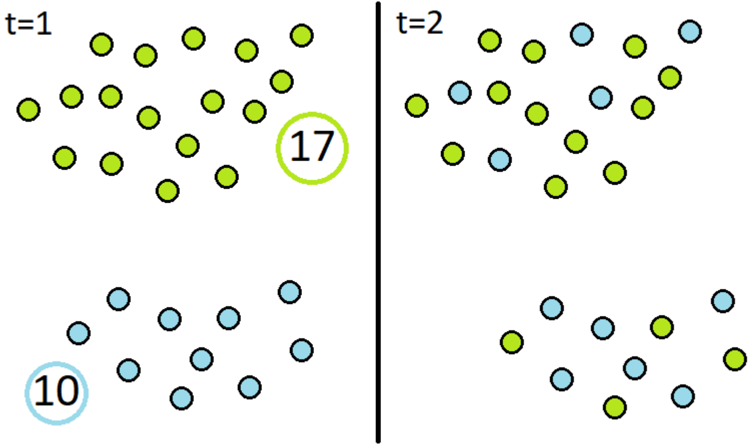

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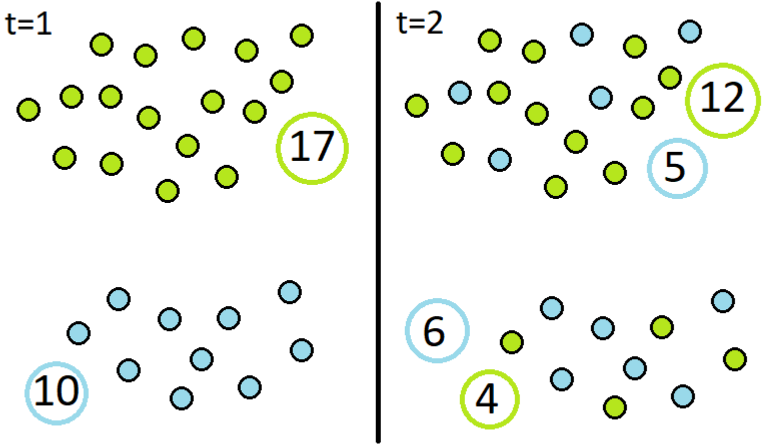

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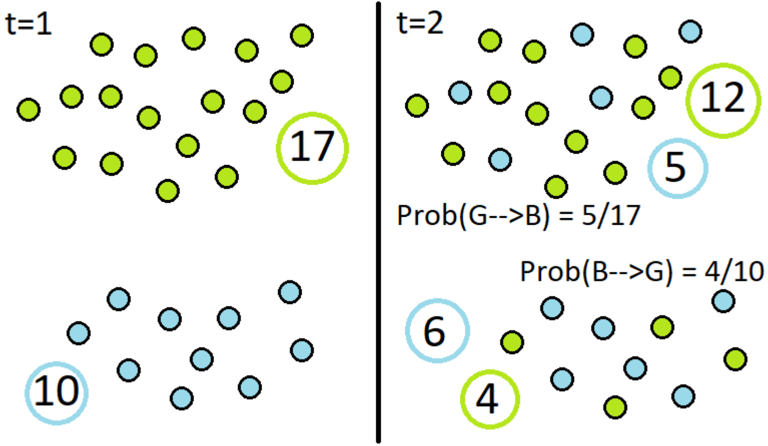


Taking SRHS transitions “straight from the data”

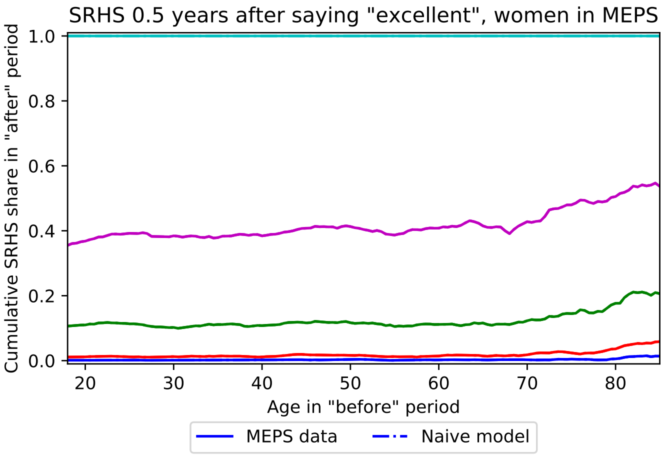
Probit or logit model:

$$y_t = \beta_0 + \beta_1 age_{t-1} + \beta_2 age_{t-1}^2 + \beta_3 sex + \beta_4 h_{t-1} + \epsilon_t,$$

$$h_t = \begin{cases} 1 & \text{if } y_t < 0 \\ 2 & \text{if } y_t \geq 0 \end{cases}.$$

Models with more than two health states use multinomial logit (e.g. Khwaja (2010))...
but always on one period transitions

Naive SRHS transitions for MEPS women: 1 wave



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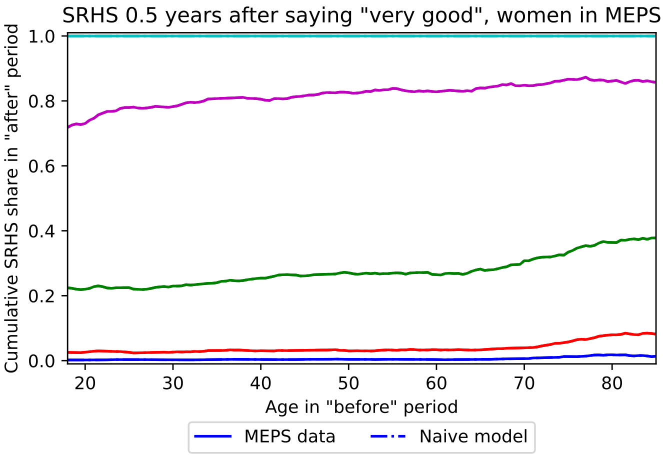

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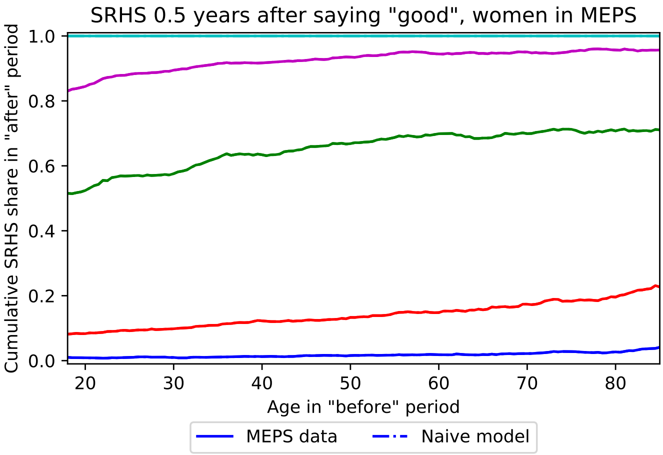

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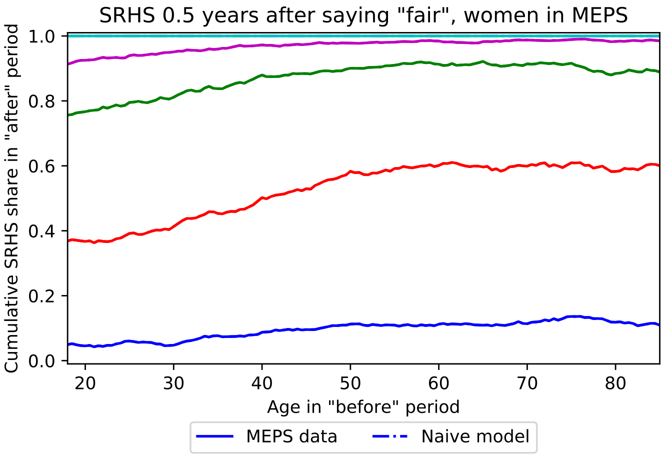

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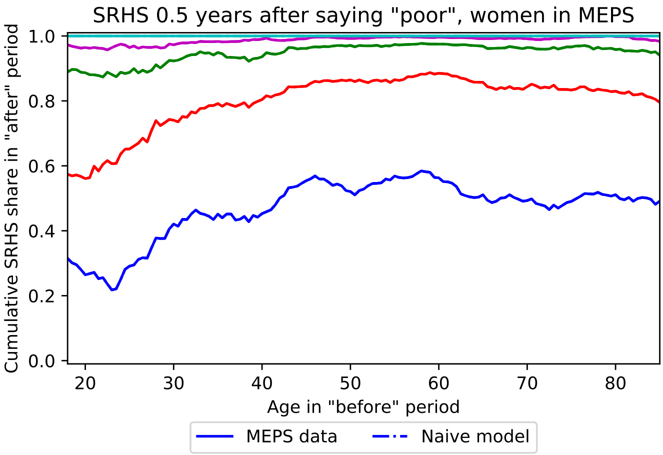

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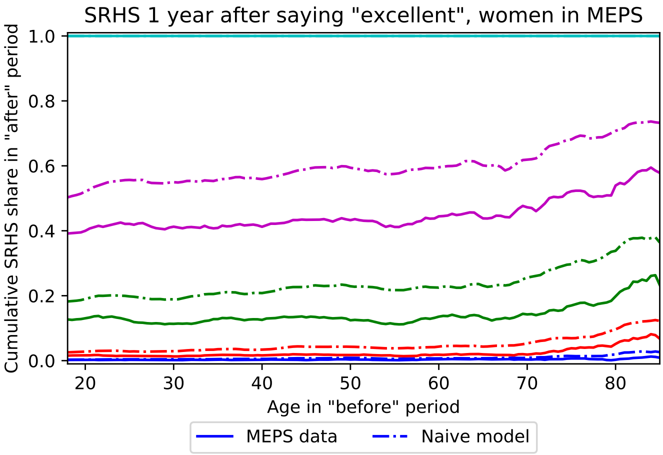

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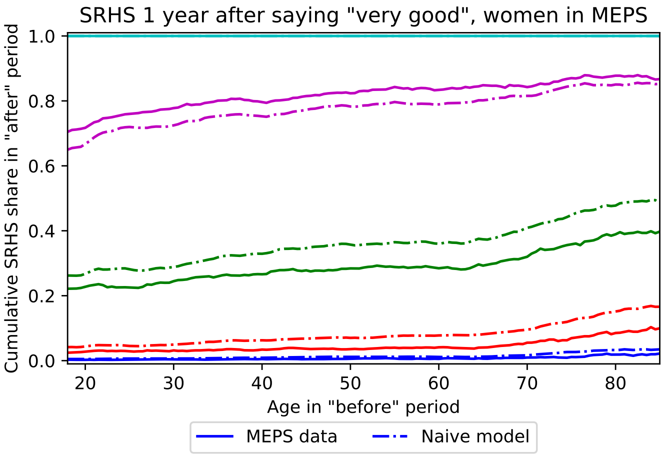

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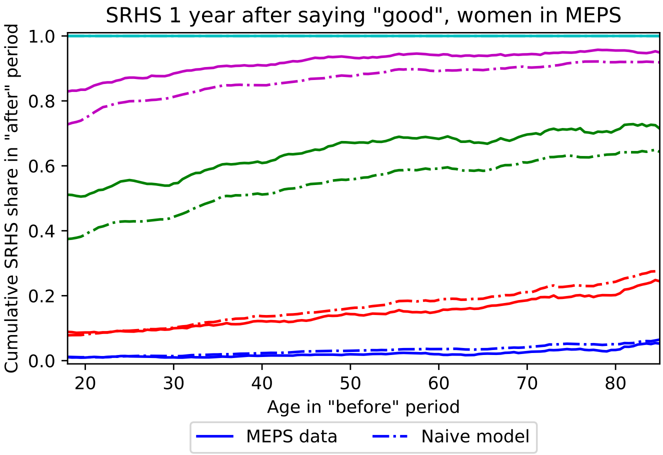

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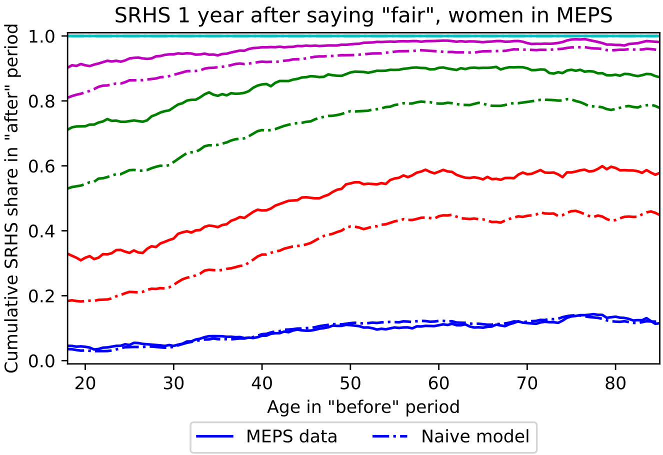

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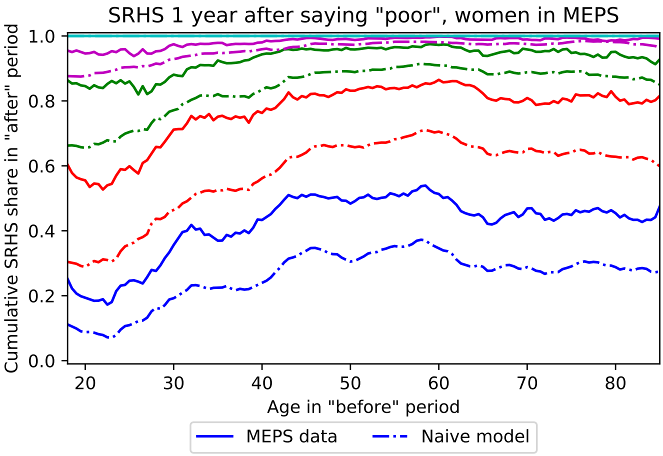

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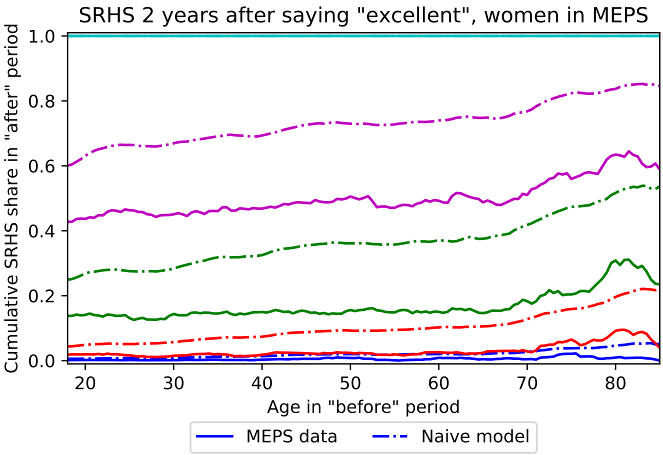

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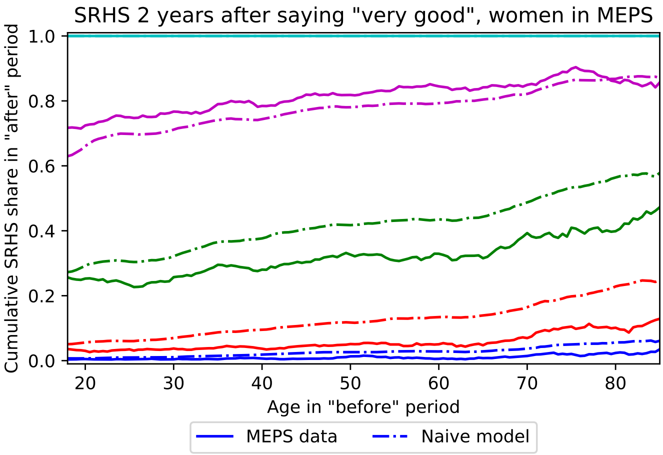

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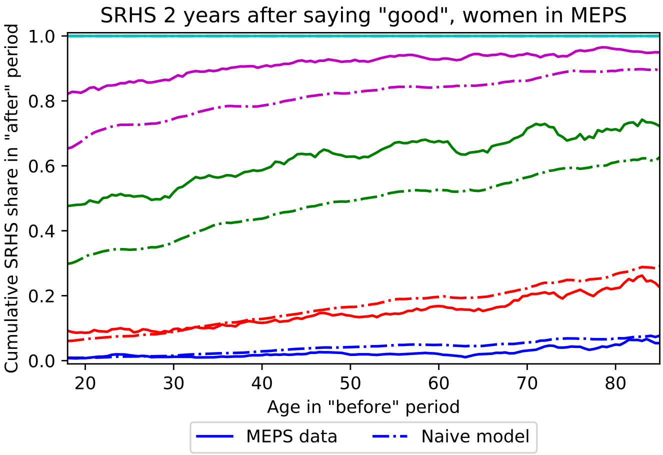

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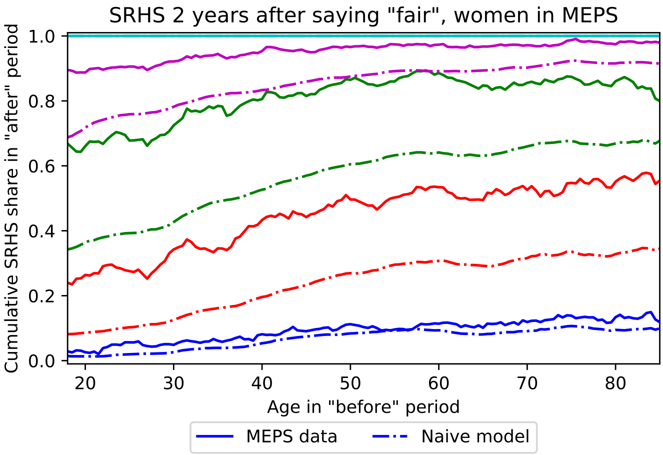

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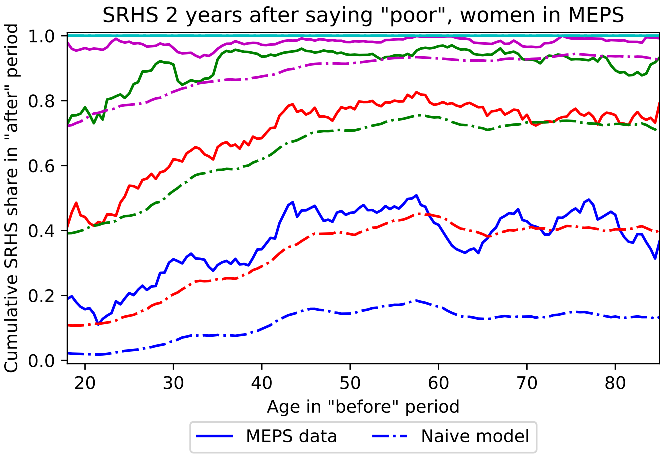

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- Who would possibly use them in “serious” work?
- What journals would publish such papers?

Who uses naive SRHS dynamics?

"We estimate the probability of death and bad health as logistic functions of a cubic in age, sex, sex interacted with age, previous health status, health status interacted with age, a quadratic in permanent income rank, and permanent income rank interacted with age."

— DeNardi, French, & Jones (2010), J. of Political Economy

Who uses naive SRHS dynamics?

"In the first [estimation] step, we estimate or calibrate parameters that can be cleanly identified without explicitly using our model. For example, we estimate mortality rates and health transitions straight from demographic data."

— French & Jones (2011), Econometrica

Who uses naive SRHS dynamics?

"To construct the transition matrix we measure the fraction of people who move from one bin to another between two consecutive years"

— Pashchenko & Porapakkarm (2013), Review of Economic Dynamics

Who uses naive SRHS dynamics?

"[S]ome parameters are estimated outside the structure of the model. For some parameters, this is because no structure is needed: disability risk can be estimated directly from transitions between disability states because of the exogeneity assumption."

— Low & Pistaferri (2015), American Economic Review

Who uses naive SRHS dynamics?

"We estimate health transitions and mortality rates simultaneously by fitting the transitions observed in the HRS to a multinomial logit model [...] on age, sex, current health status, and PI."

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Who uses naive SRHS dynamics?

"We estimated the transition probabilities using the logit method. We regressed next period's health status on a constant, age, age squared, age cubic, education level, current health status, and age times current health status."

— Ferreira & Gomes (2017), Review of Economic Dynamics

Who uses naive SRHS dynamics?

"The transition to next period health status is determined as a logistic function of [math notation]."

—Aizawa (forthcoming), Quantitative Economics

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- Problem: That's just not true

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SRHS is not Markov(1) (3/3)

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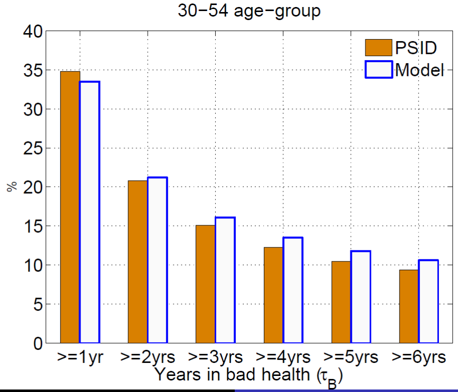

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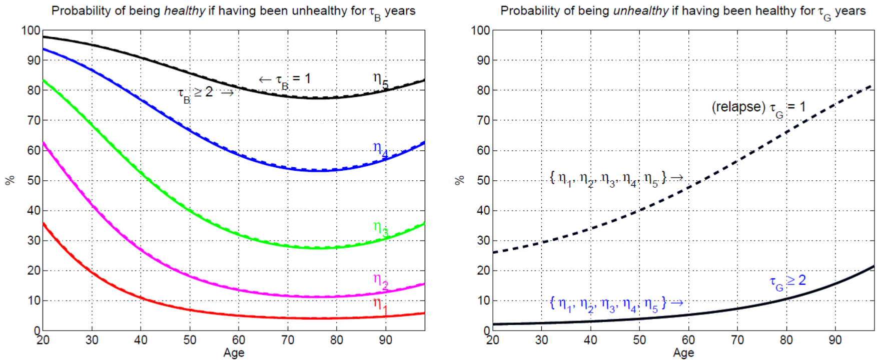

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- Mean log medical costs for "healthy": 6.82
  - ...and "unhealthy" one year prior: 7.14
  - ...and "healthy" one year prior: 6.79
- **Lagged SRHS generates observably different medical expense distributions; "unhealthy" people are not all in the same health state!**

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- **Wave 1 SRHS is nearly as predictive of W5 SRHS as it is for W2 SRHS!**

But it's not duration dependence (3/3)

- Suppose you saw these examples, but the labels were "in bottom income quintile" and "above bottom income quintile"

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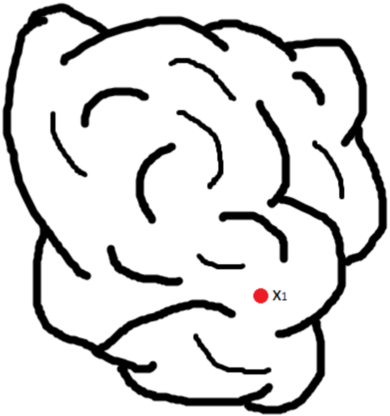
MODEL

Graphical model of latent health and SRHS (1/5)

"True health" lives in some weird polydimensional space



Graphical model of latent health and SRHS (2/5)

Dynamics of "true health" really **are** Markov(1)

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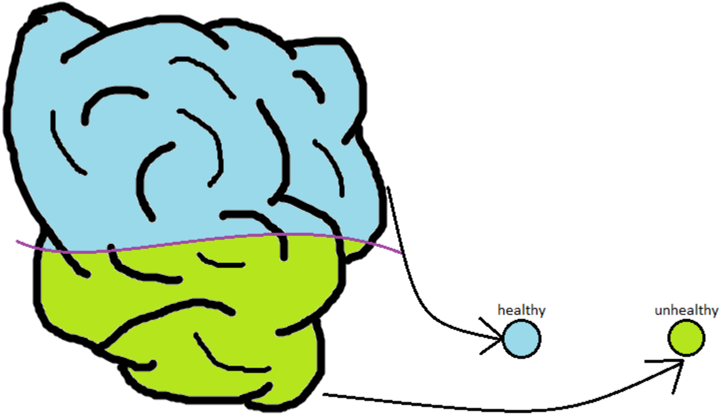
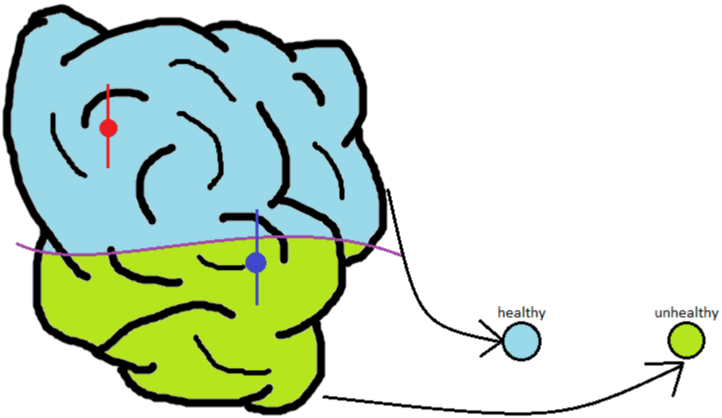


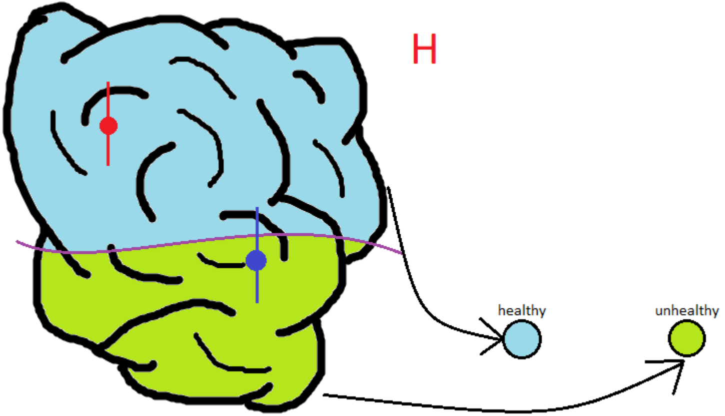
Graphical model of latent health and SRHS (3/5)

SRHS is a projection of that polydimensional space onto a discrete space... with reporting error



Graphical model of latent health and SRHS (4/5)

Individuals whose "true health" is far from the healthy/unhealthy threshold are likely to have the same SRHS period after period



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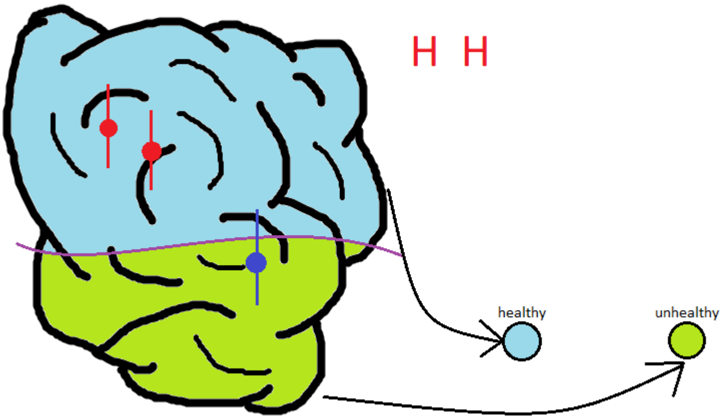

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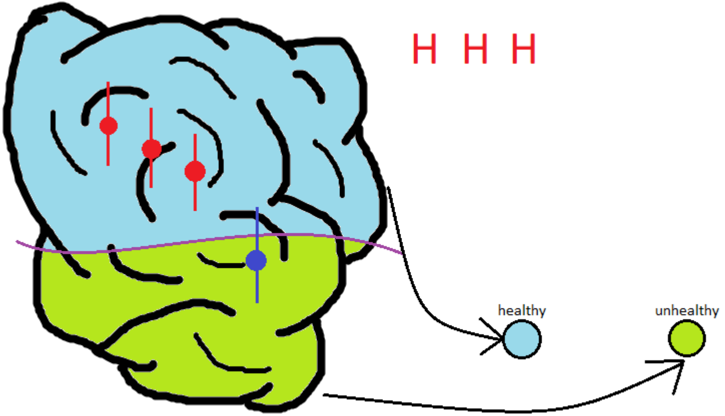

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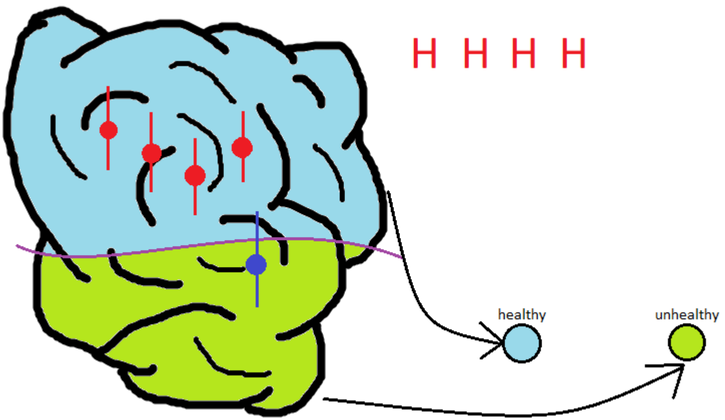

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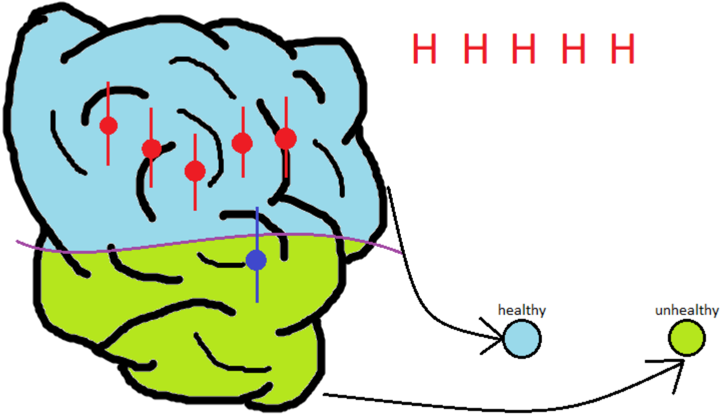

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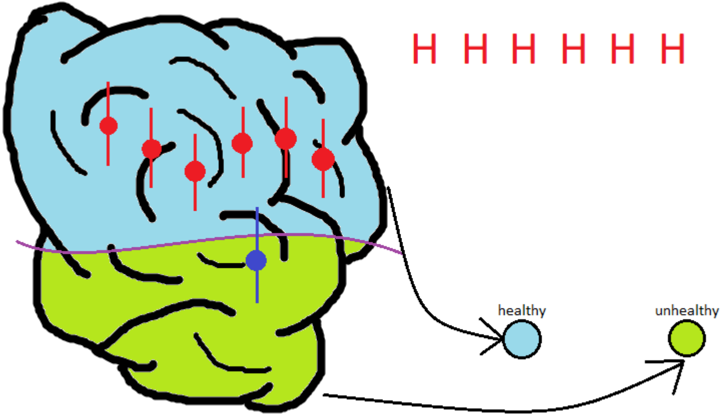

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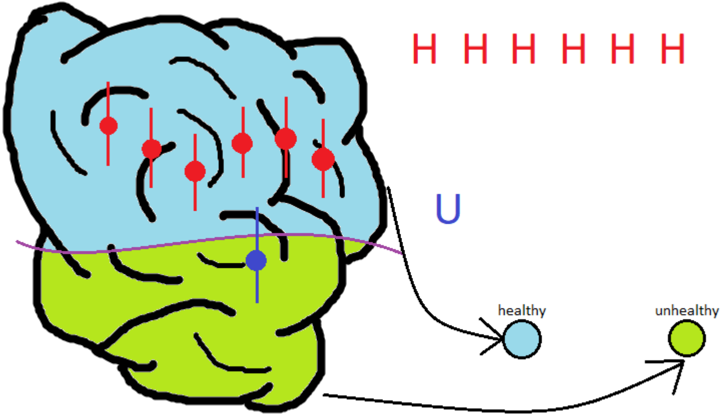

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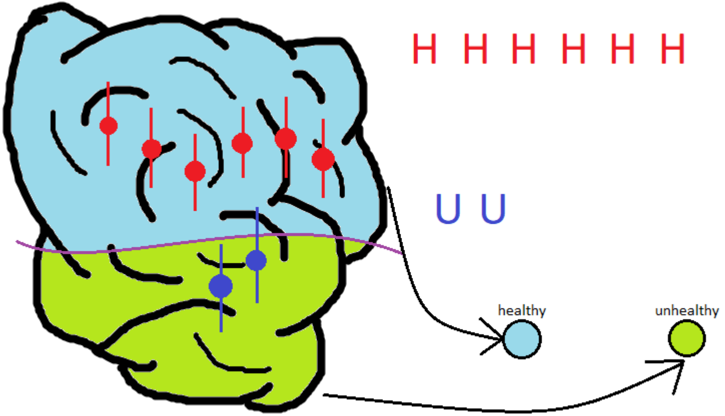

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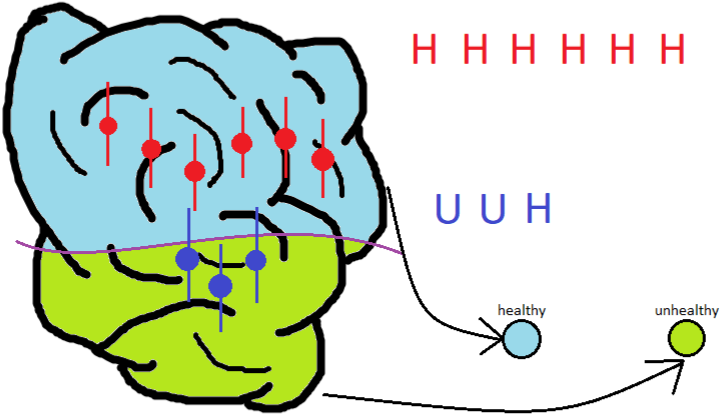

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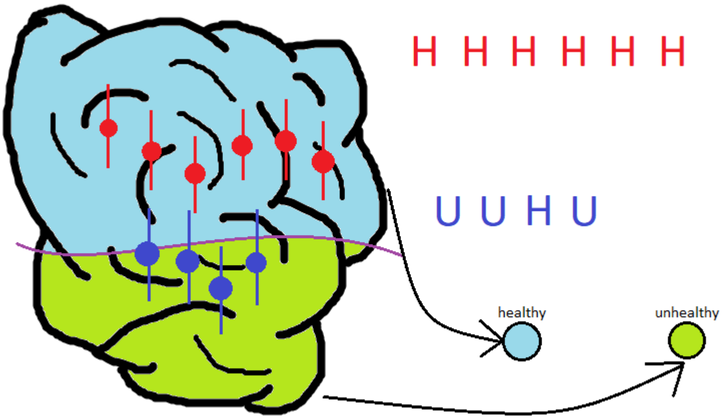

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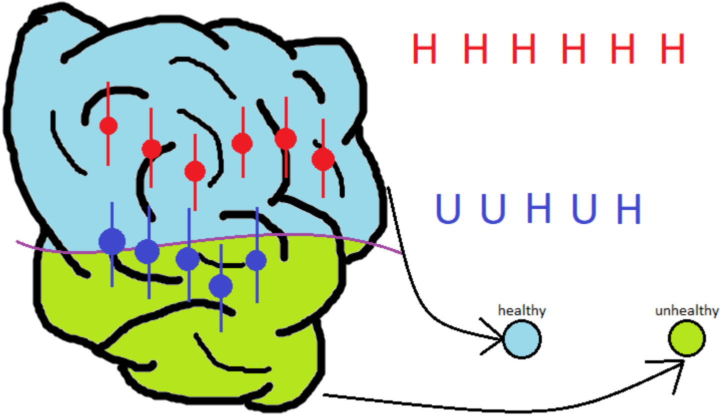

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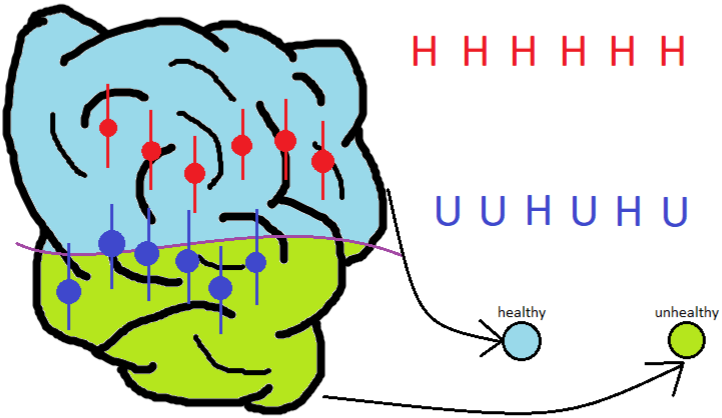

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- Early 40's women: 37-38% change SRHS from their answer a couple weeks prior if reported poor to very good health; 44% change answer if reported excellent health

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- All parameters can differ between men and women.
- No reporting error for mortality.
- No selection in attrition or missing SRHS.

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- Using (1-3), can precompute **unconditional** pmf of x_t at every age (i.e. simulation by multiplication)

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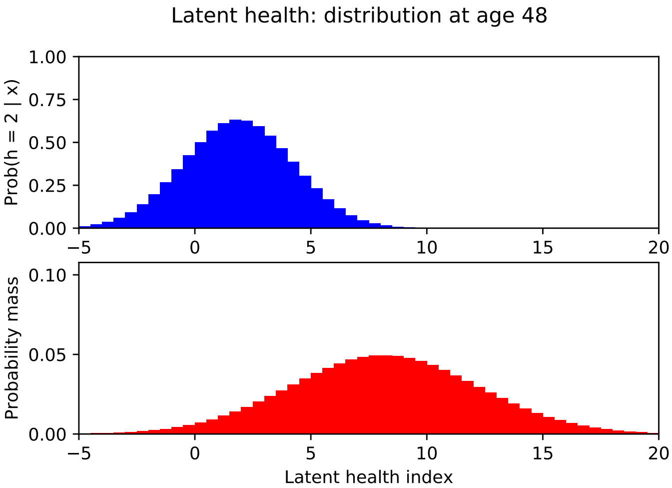

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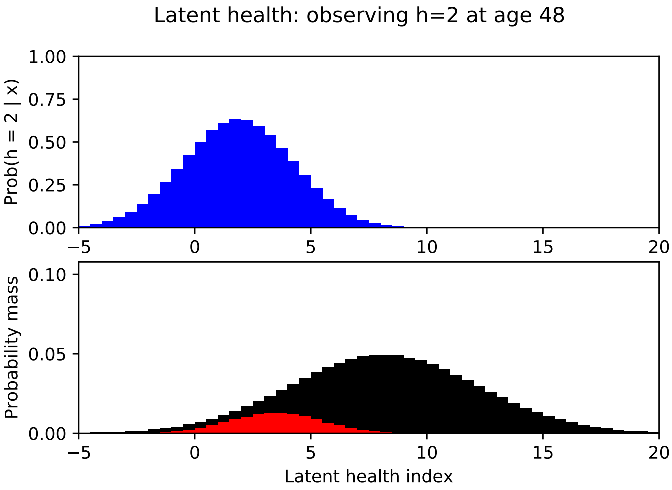

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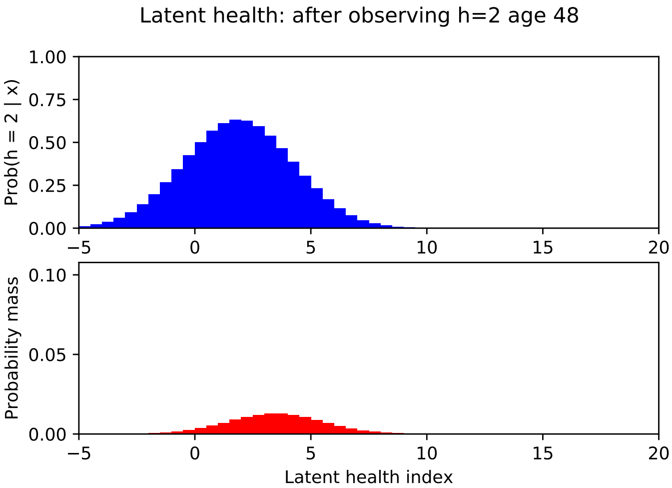

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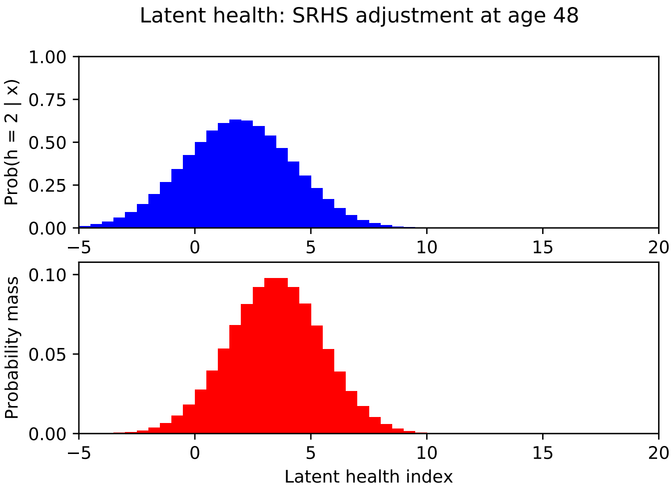

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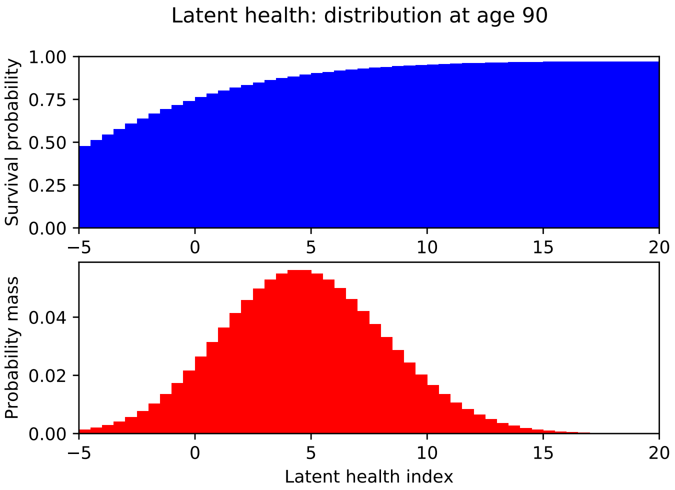

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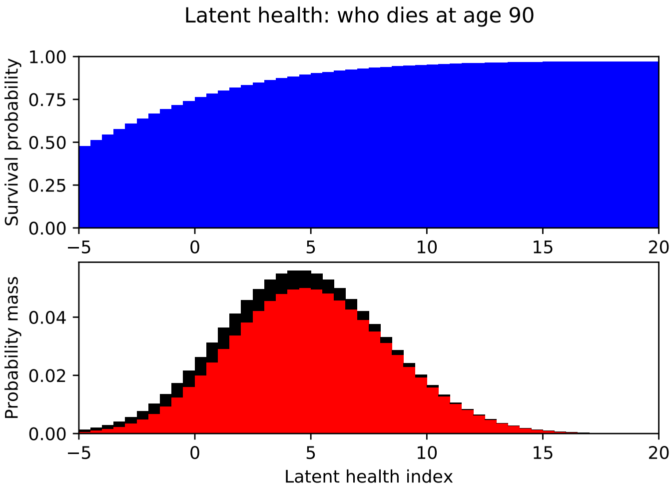

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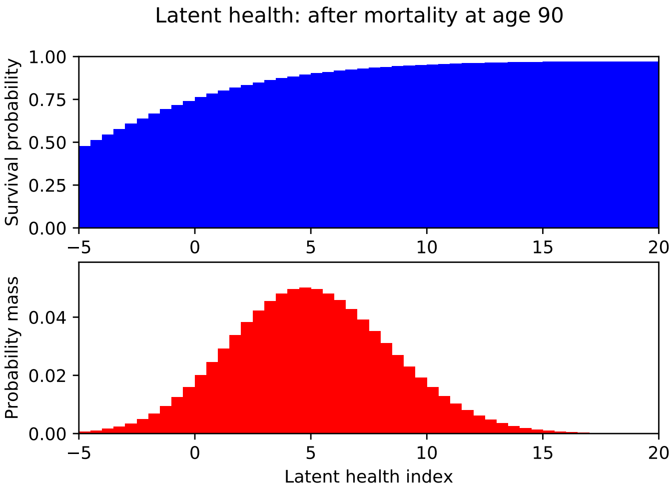

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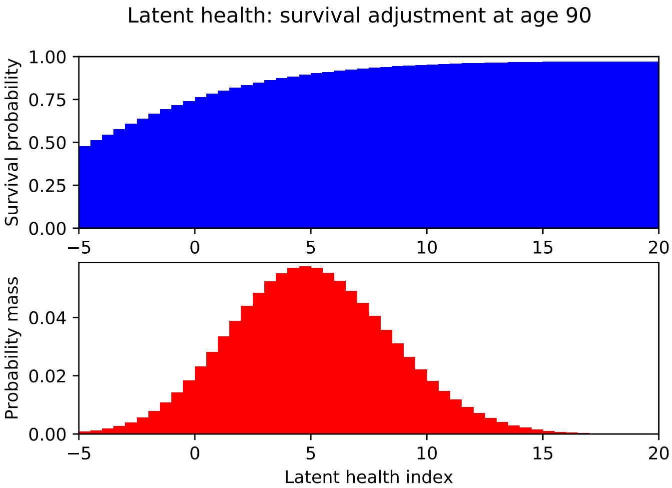

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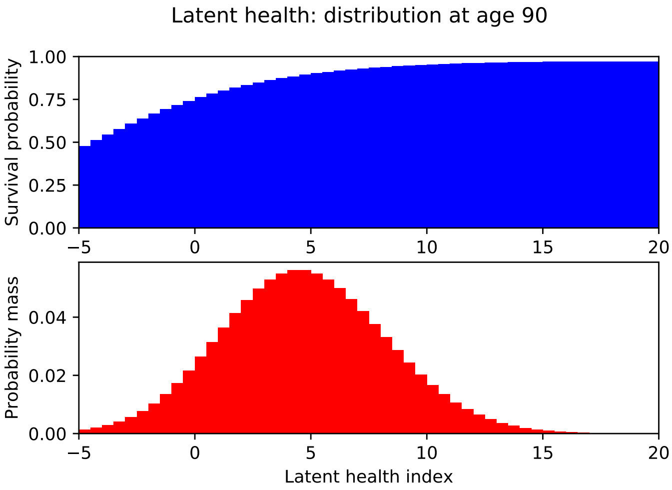

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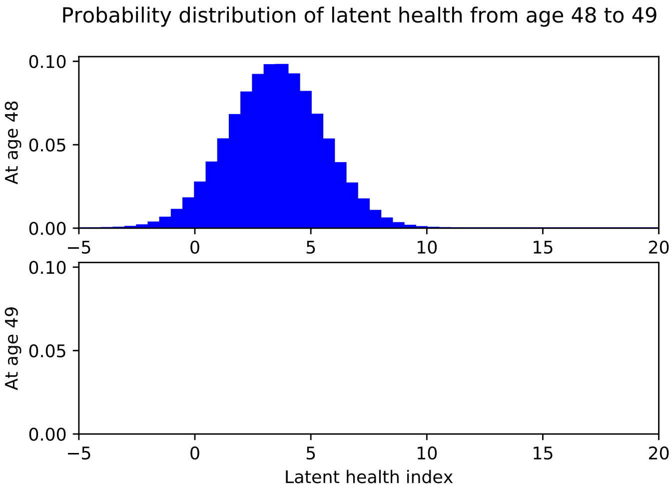

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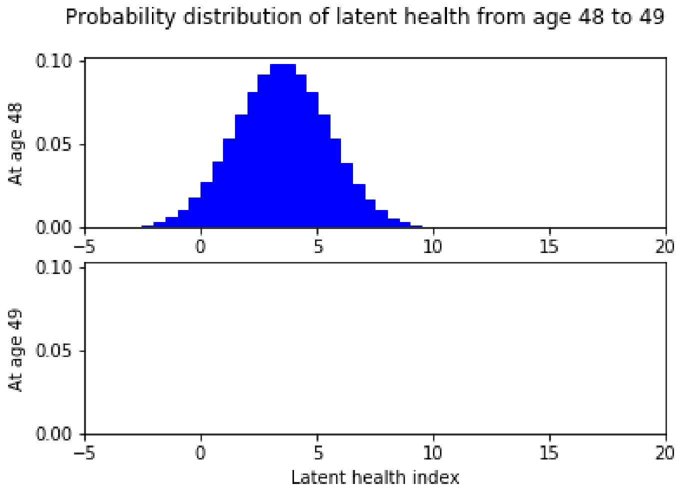

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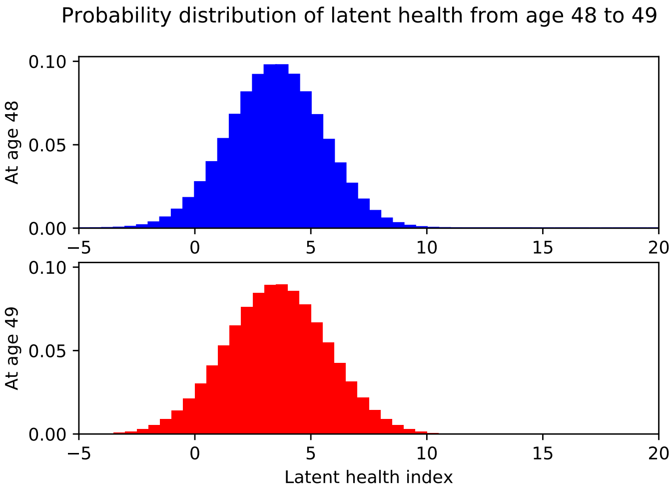

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- Need more than 2 SRHS categories to do this!

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- Identify expected health parameters β, initial health distribution (μ_0, σ_0^2), and probit cut points χ from distribution of SRHS by age

DATA

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- Drop under 18's and over 84's (age is topcoded at 85)
- Relabel age to have half-years based on age in W1 and W2
- 126,486 women observed for 601,713 waves (1,168 deaths)
- 110,044 men observed for 518,577 waves (1,314 deaths)
- 89% of respondents observed all 5 waves; most others drop after 3 (maybe planned drops?)

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- Observe SRHS every 2 years; recoded to 1 year periods
- 20,108 women observed for 107,542 waves (5,794 deaths)
- 16,094 men observed for 81,091 waves (5,286 deaths)
- 50% observed alive at least 5 waves, 11% obs all 11 waves

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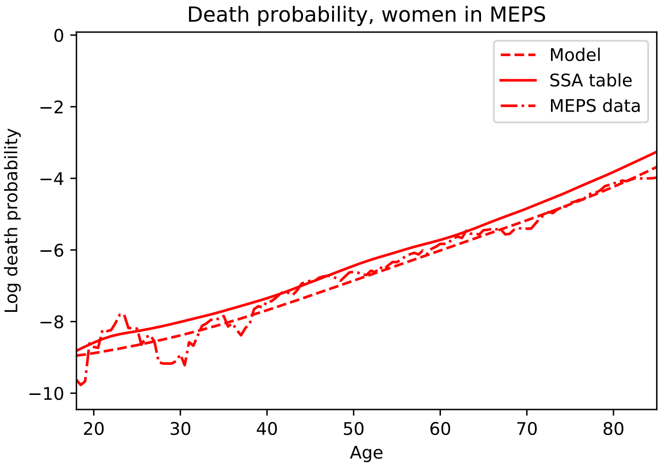
- SRHS **only** asked of HH heads and spouses
- Selection bias: college students aren't heads yet!
- Enter my data at age 23; also drop R's who start 90+
- 11,787 women observed for 69,329 waves (1,012 deaths)
- 10,791 men observed for 58,316 waves (995 deaths)
- 32% observed 2 waves or fewer, but 22% obs all 11 waves

RESULTS

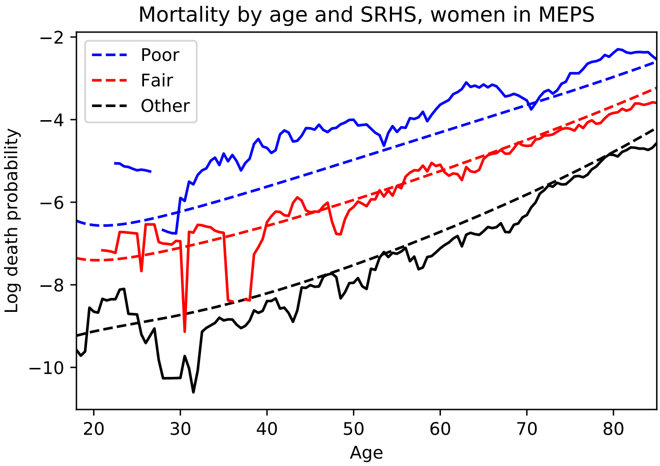
Estimated parameters: MEPS women (mortality)

Param	Description	MEPS
θ_0	Mortality probit: constant term	2.667
		(9.96e-2)
θ_{x1}	Mortality probit: linear coefficient on health	0.116
		(4.65e-3)
θ_{x2}	Mortality probit: quadratic coefficient on health	-5.51e-4
		(2.51e-4)
θ_{j1}	Mortality probit: linear coefficient on age	1.29e-2
		(3.38e-3)
θ_{j2}	Mortality probit: quadratic coefficient on age	-3.43e-4
		(3.19e-5)
θ_{j3}	Mortality probit: cubic coefficient on age	2.80e-7
		(1.10e-7)
θ_{xj}	Mortality probit: coefficient on age$\times$health	1.24e-4
		(3.77e-5)

Model fit: Mortality by age for MEPS women



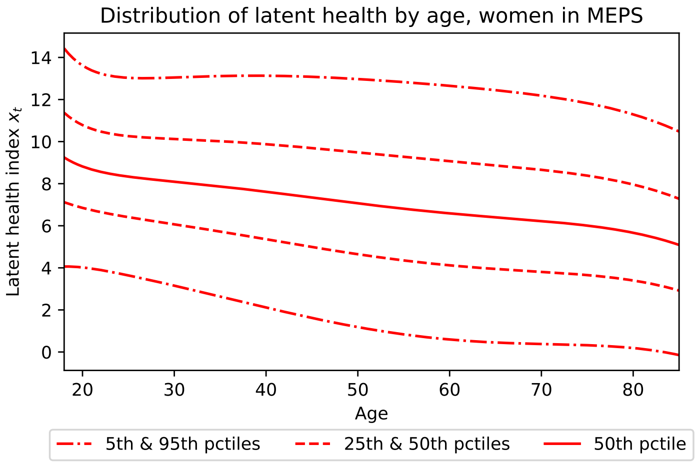
Model fit: Mortality by age and SRHS for MEPS women



Estimated parameters: MEPS women (latent health)

Param	Description	MEPS
β_0	Expected health: constant term	-1.067
		(0.295)
β_{j1}	Expected health: linear coefficient on age	0.974
		(3.19e-2)
β_{j2}	Expected health: quadratic coefficient on age	-3.57e-2
		(1.27e-3)
β_{j3}	Expected health: cubic coefficient on age	5.18e-4
		(2.13e-5)
β_{j4}	Expected health: quartic coefficient on age	-2.68e-6
		(1.25e-7)
μ_0	Mean of latent health at model start	9.383
		(8.80e-2)
σ_0	Standard deviation of latent health at model start	3.160
		(4.47e-2)

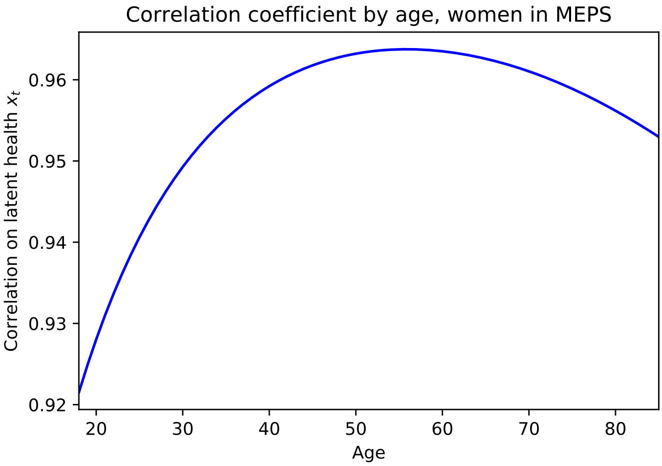
Estimated model: Distribution of latent health (MEPS women)



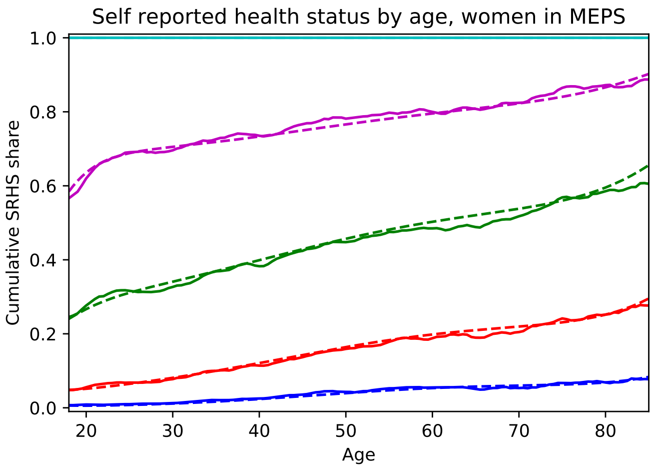
Estimated parameters: MEPS women (correlation and SRHS)

Param	Description	MEPS
γ_0	Correlation factor: constant term	1.262 (9.87e-2)
γ_{j1}	Correlation factor: linear coefficient on age	8.54e-2 (6.71e-3)
γ_{j2}	Correlation factor: quadratic coefficient on age	-1.11e-3 (1.43e-4)
γ_{j3}	Correlation factor: cubic coefficient on age	4.15e-6 (9.65e-7)
α_1	SRHS: Linear coefficient on latent health	0.503 (5.33e-3)
χ_2	SRHS: Cut b/w reporting "fair" and "good"	1.596 (6.90e-3)
χ_3	SRHS: Cut b/w reporting "good" and "very good"	3.389 (9.82e-3)
χ_4	SRHS: Cut b/w reporting "very good" and "excellent"	5.112 (1.28e-2)

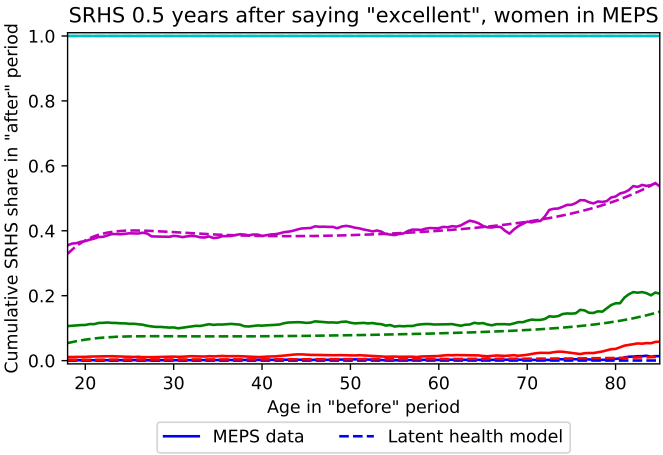
Estimated model: Latent health serial correlation (MEPS women)



Model fit: SRHS by age for MEPS women



Model fit: SRHS transitions for MEPS women: 1 wave



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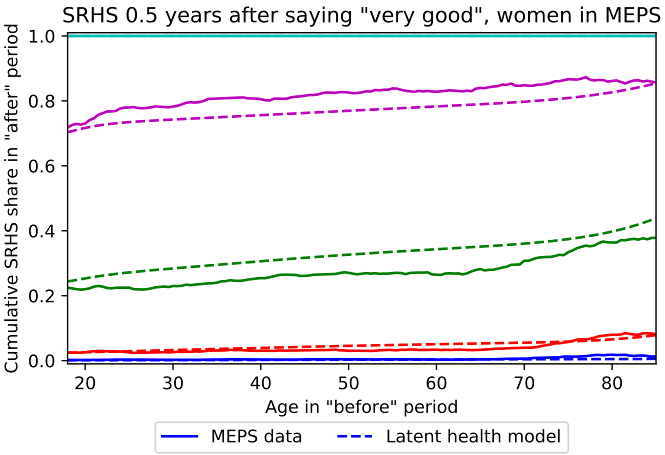

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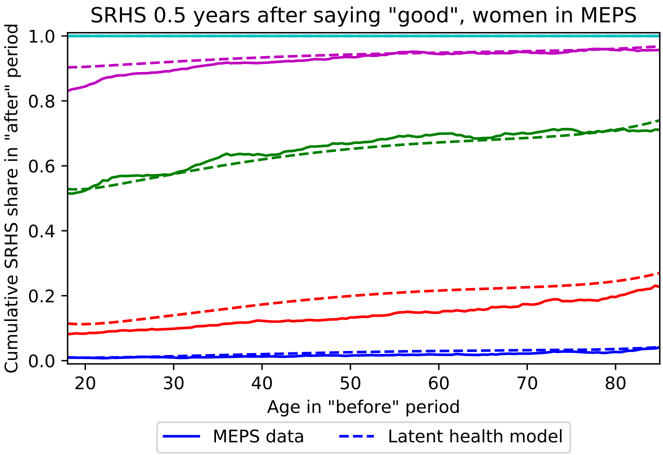

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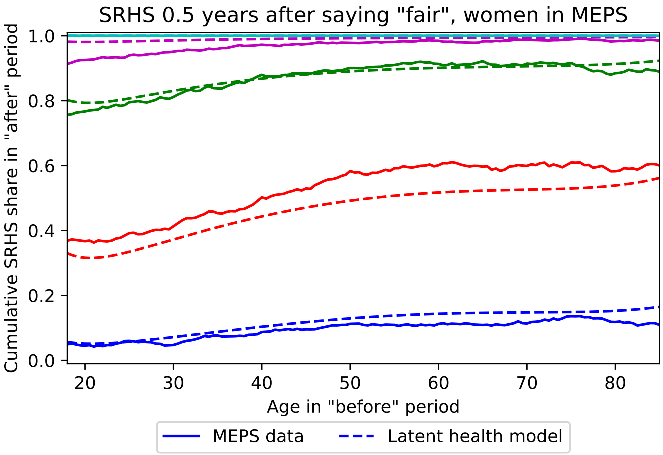

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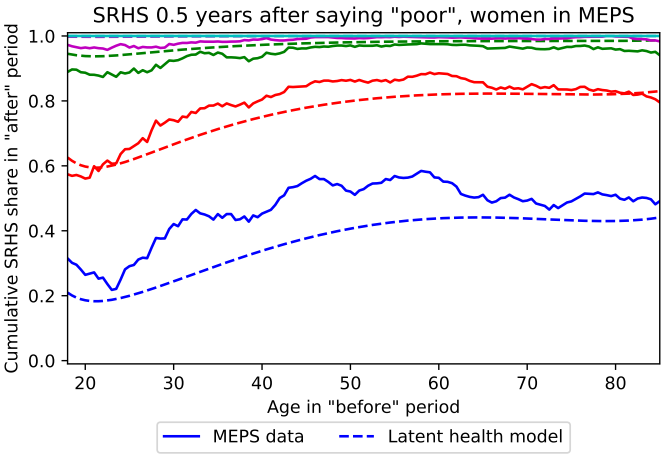

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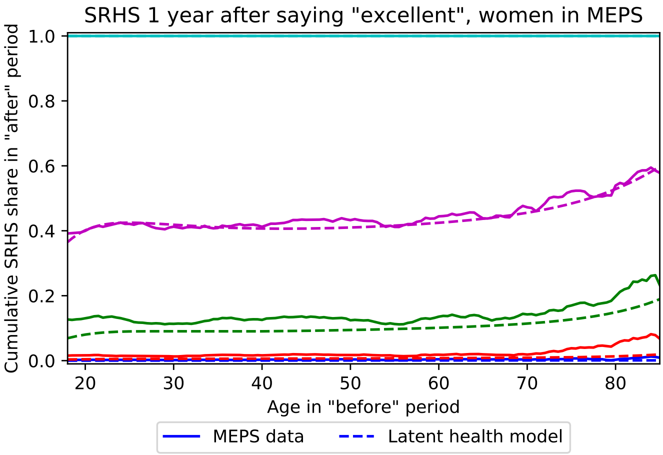

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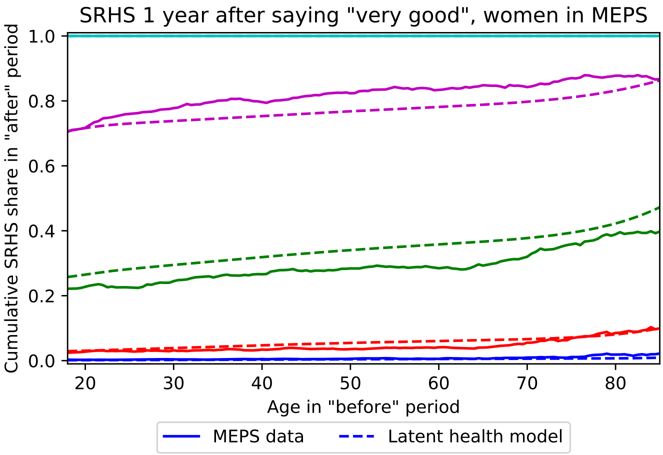

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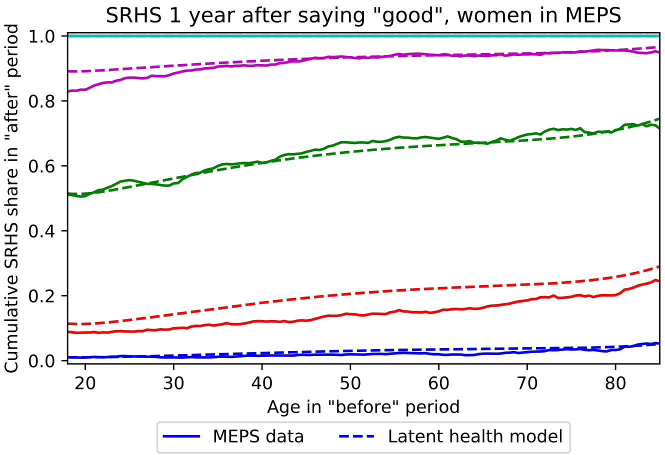

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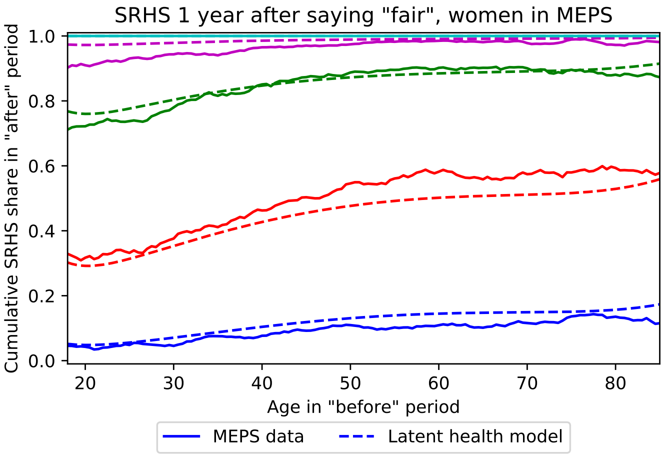

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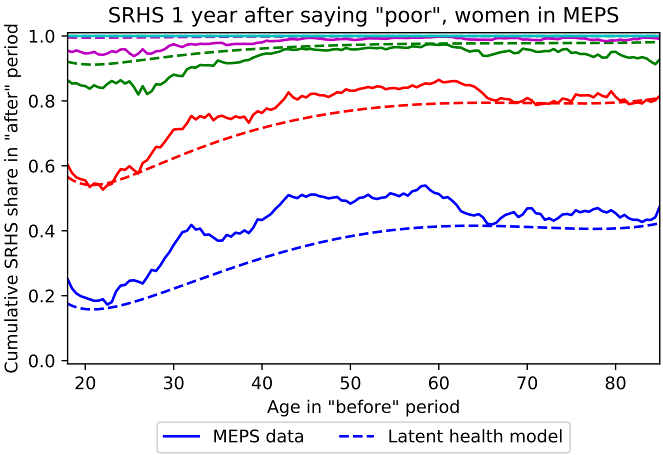

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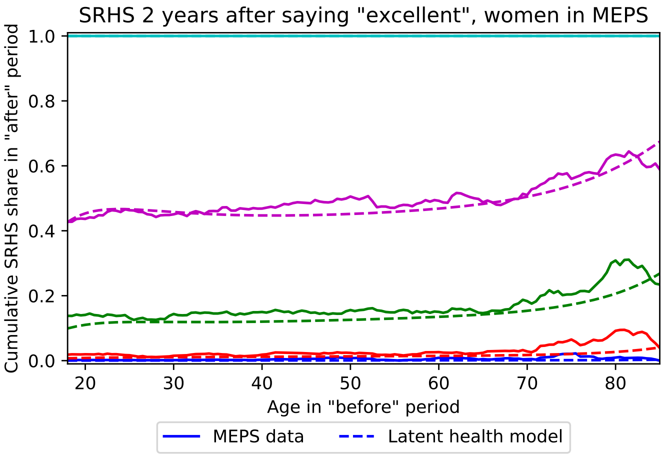

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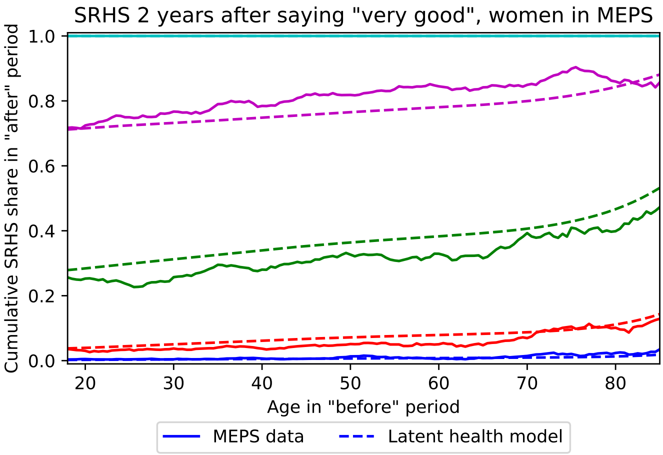

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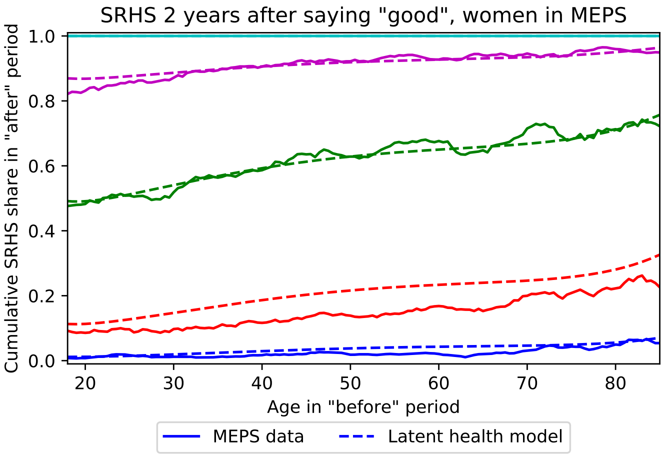

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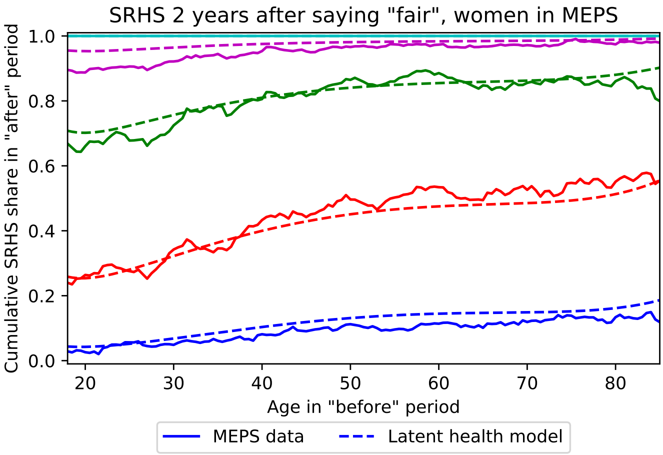

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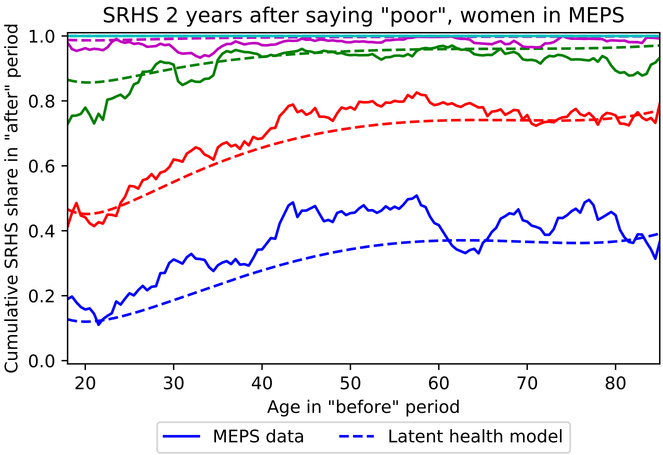

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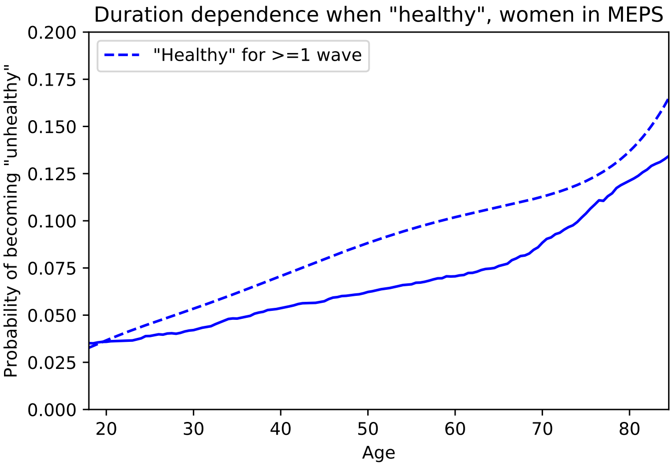

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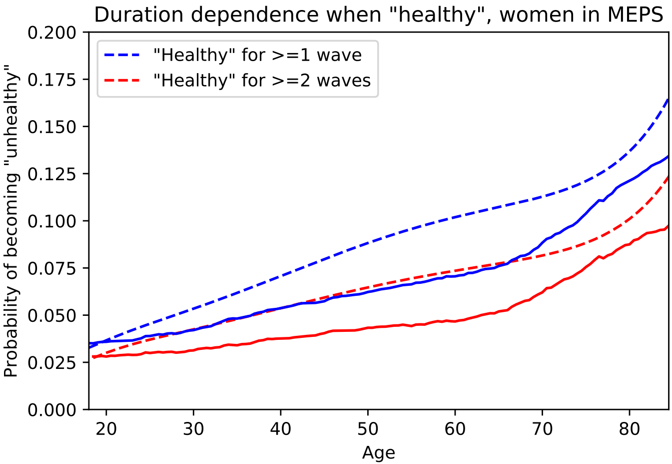

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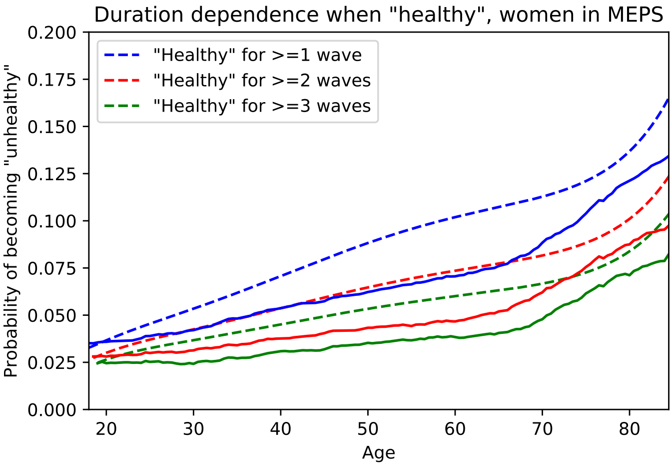

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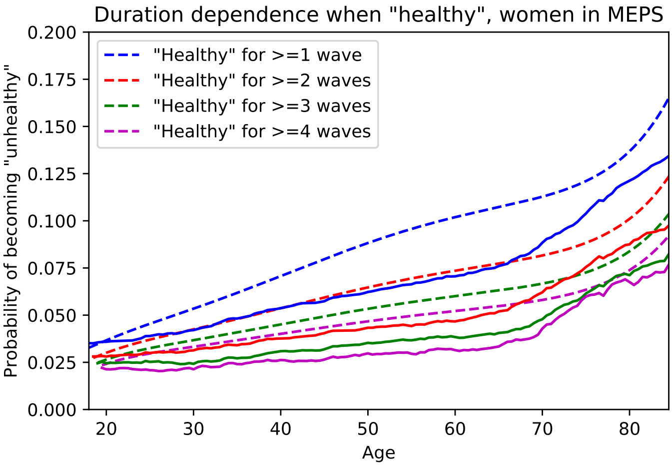

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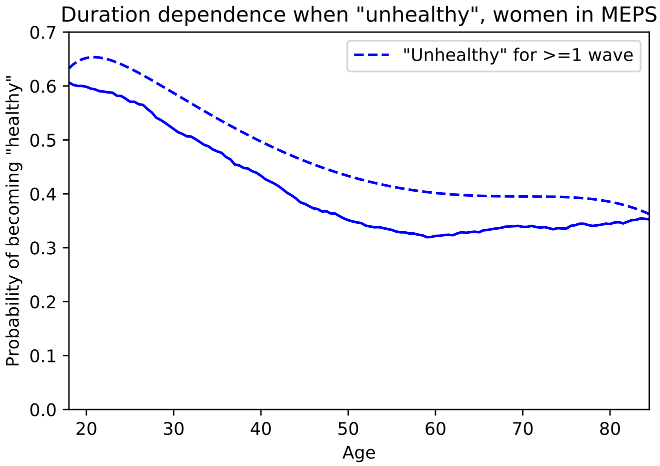

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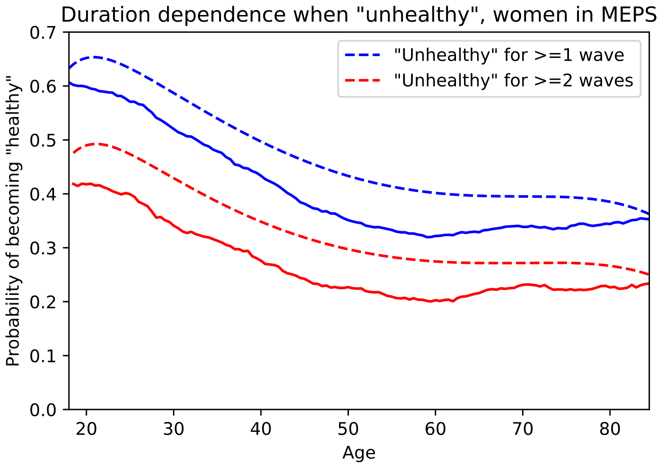

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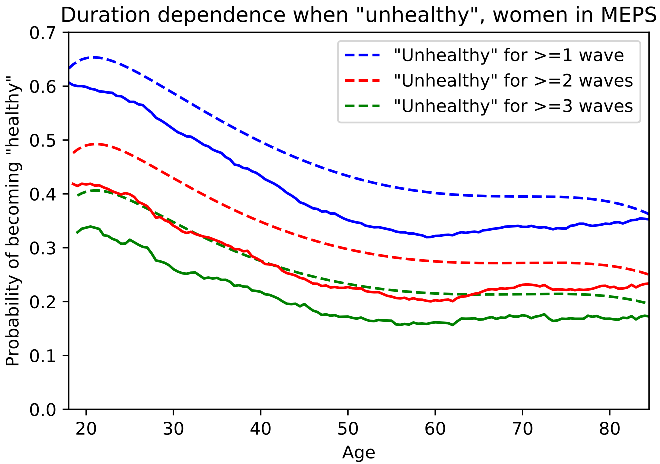

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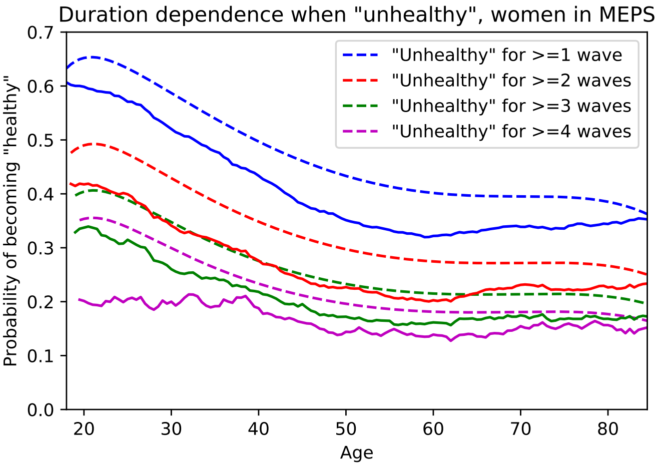
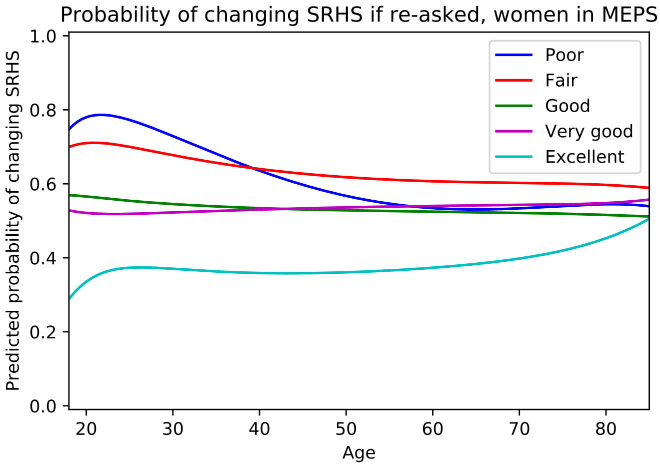


Estimated model: Changing SRHS if asked twice (MEPS women)



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- Same exercise for men: $R^2 = 0.2326$ (latent health) vs $R^2 = 0.2326$ (full interact)

Estimated model: Out-of-sample fit

- Also estimated model on PSID and HRS, men and women; all fit well
- Model was estimated on **short panel** MEPS data and fit it well...
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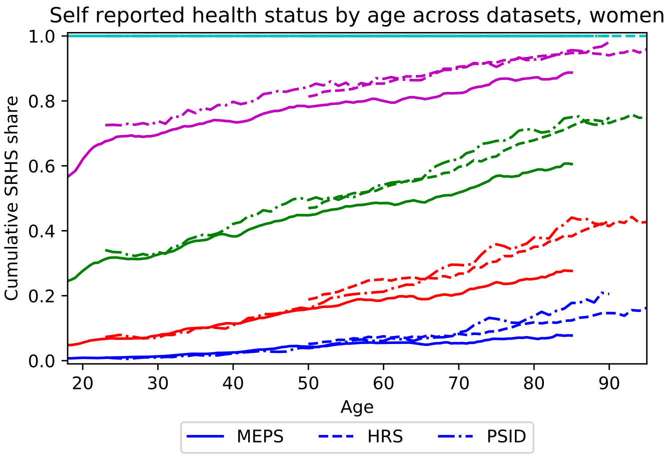
- Result: **No, it absolutely does not fit**
- Probably too much of a stretch to project a model 10x beyond data
- MEPS has a selection bias problem: too few respondents in poor health
- And asks respondents to compare to people of their own age

SRHS across datasets: MEPS, HRS, and PSID (women)



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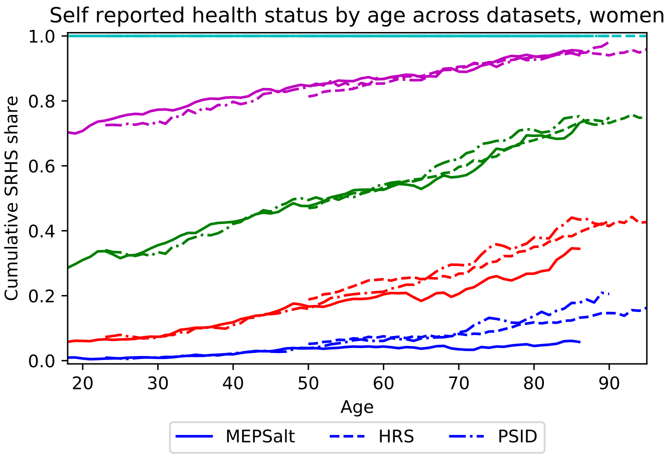
- Only admit PSID respondents when they turn 23
- 120,055 women observed for 342,796 waves (6,918 deaths)
- 102,965 men observed for 281,681 waves (6,568 deaths)
- 82% of respondents observed 2 or fewer waves (mostly MEPS)

SRHS across datasets: MEPS-SAQ, HRS, and PSID (women)



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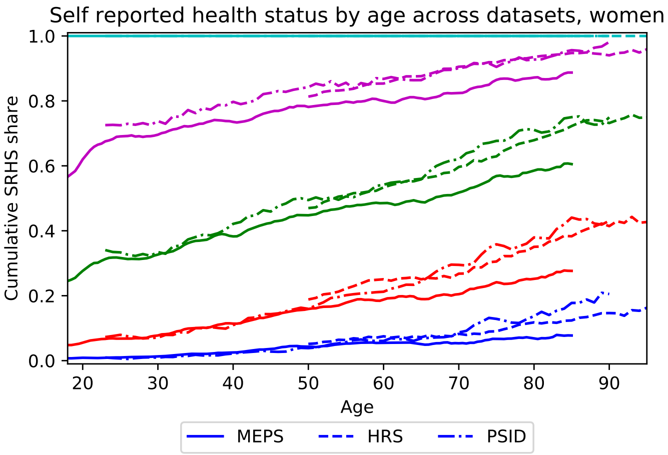
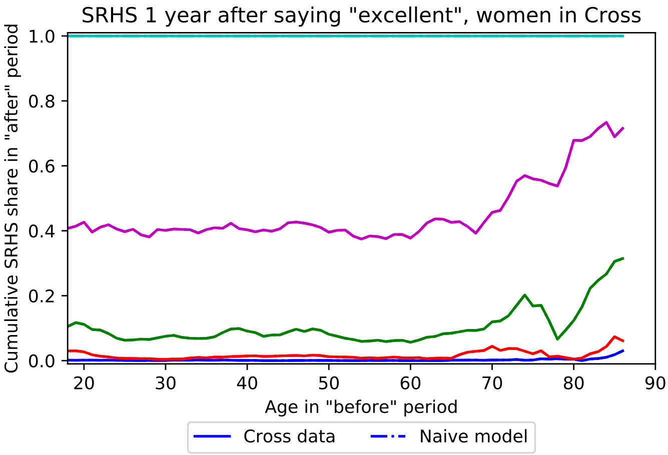


Naive SRHS transitions for cross-data women: 1 year



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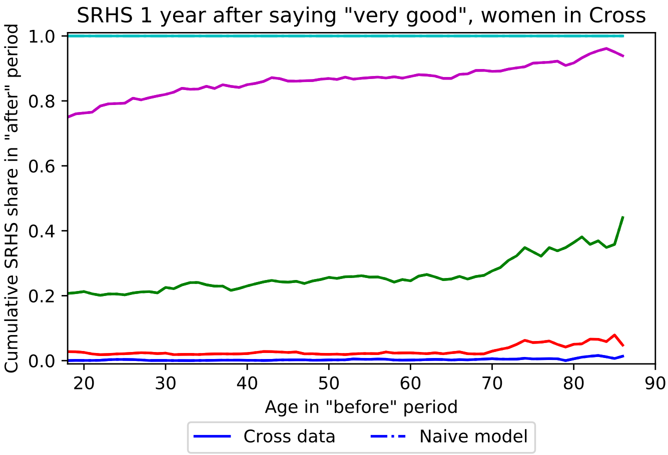

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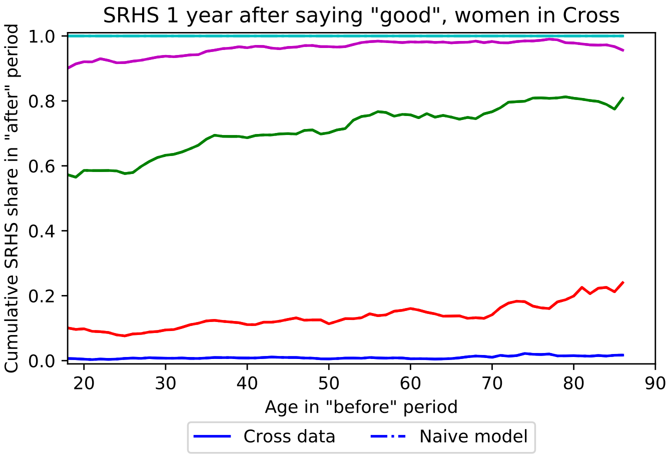

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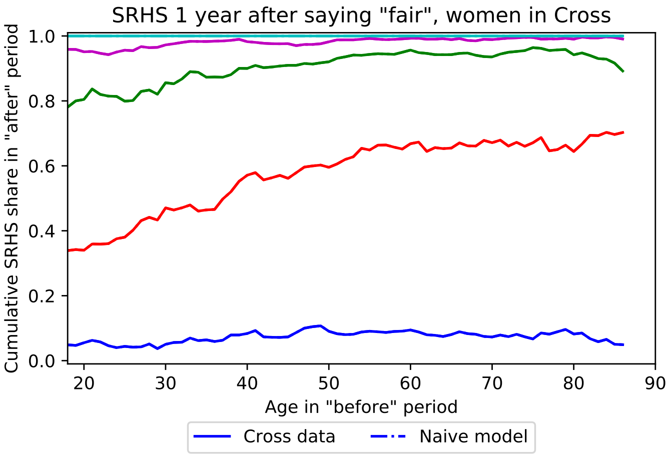

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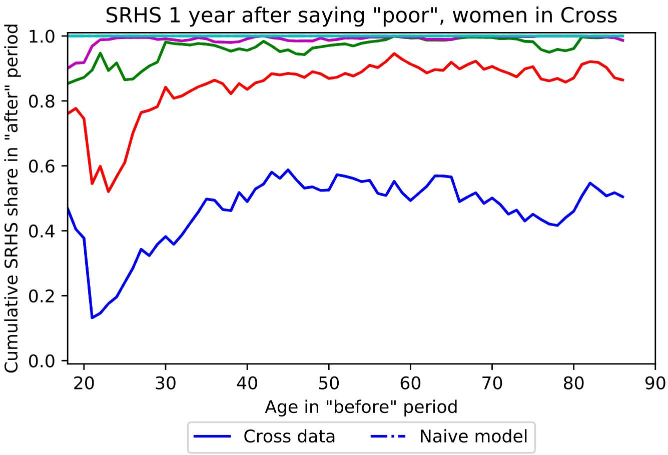
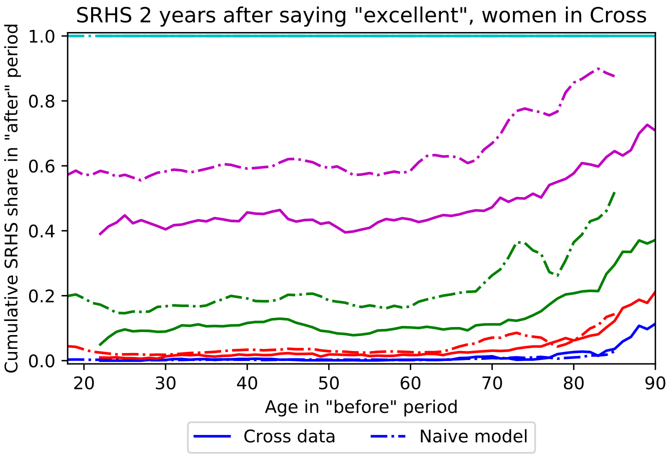
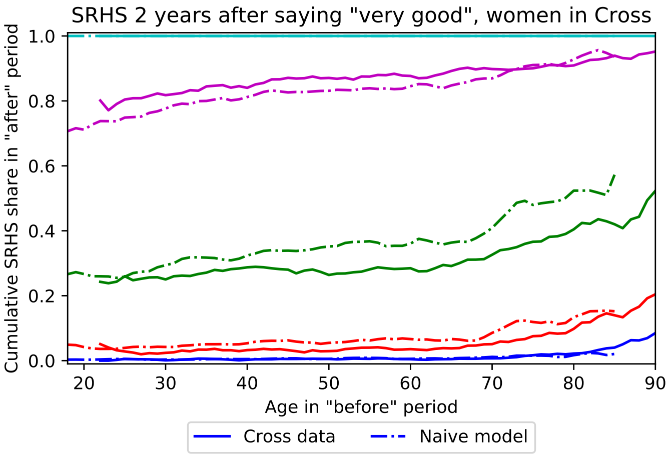


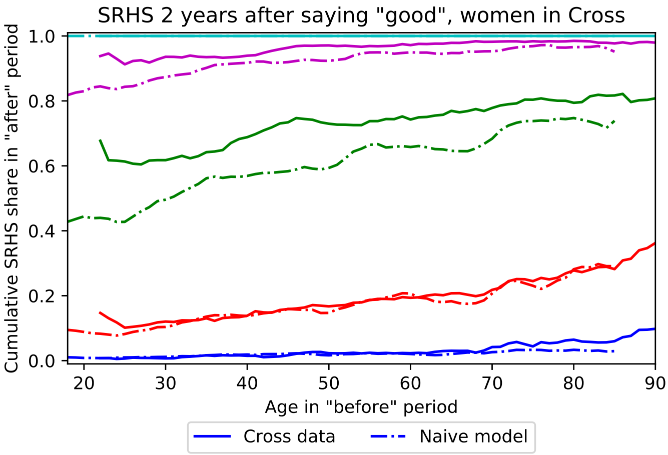
Naive SRHS transitions for cross-data women: 2 years



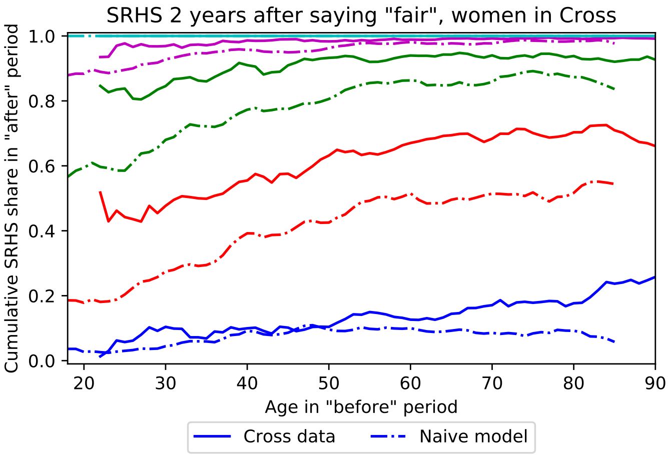
Naive SRHS transitions for cross-data women: 2 years



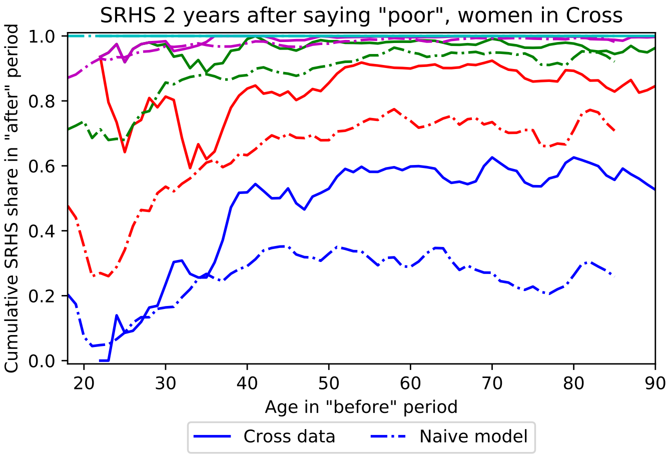
Naive SRHS transitions for cross-data women: 2 years



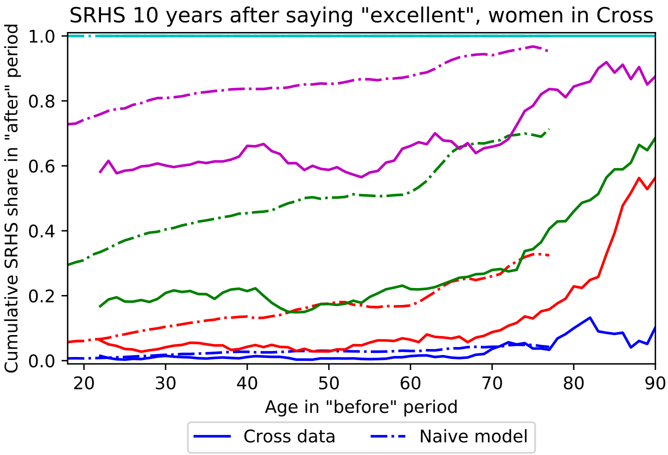
Naive SRHS transitions for cross-data women: 2 years



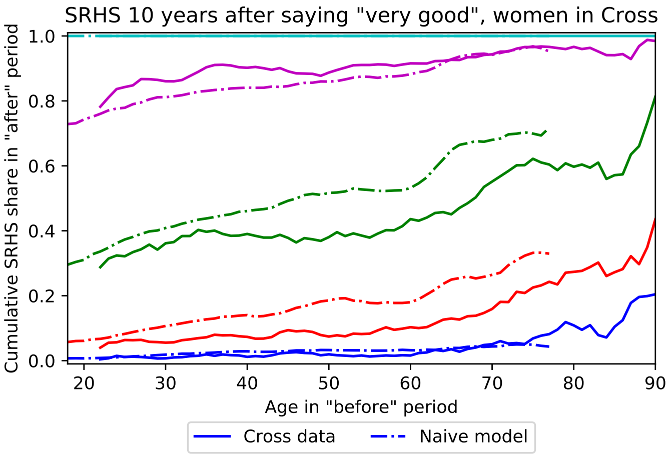
Naive SRHS transitions for cross-data women: 2 years



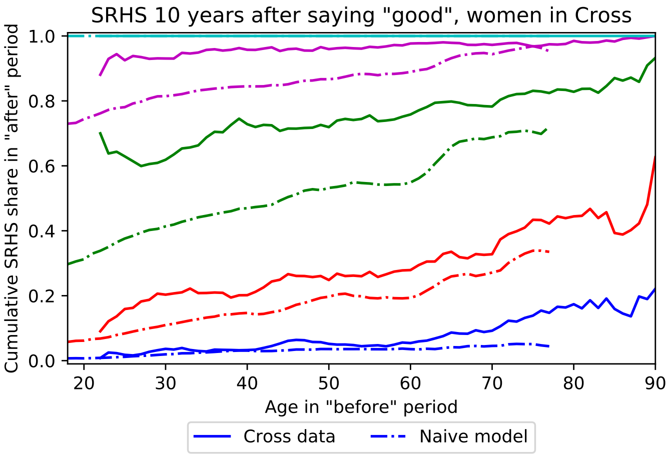
Naive SRHS transitions for cross-data women: 10 years



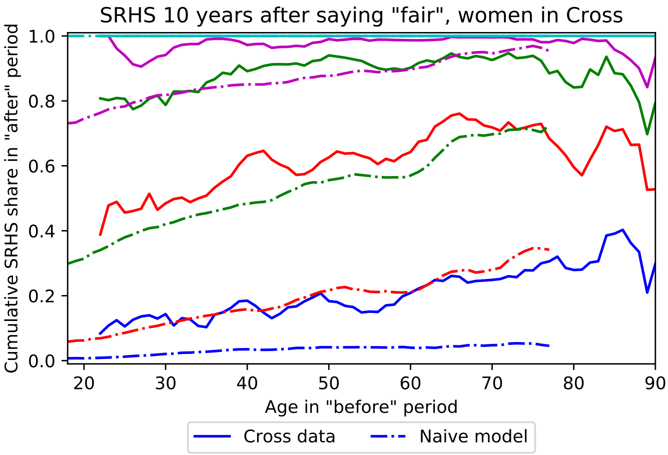
Naive SRHS transitions for cross-data women: 10 years



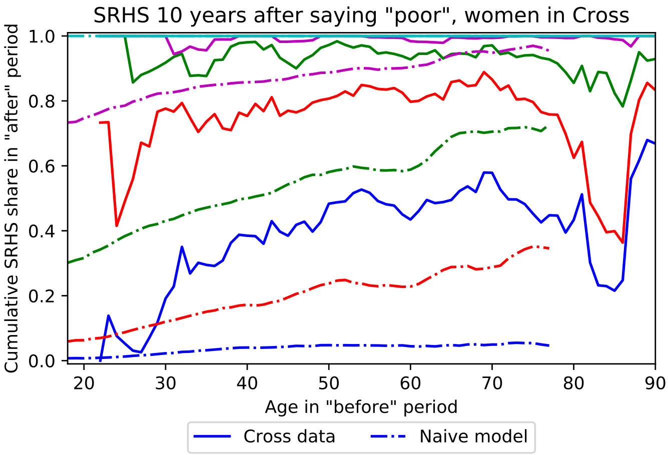
Naive SRHS transitions for cross-data women: 10 years



Naive SRHS transitions for cross-data women: 10 years



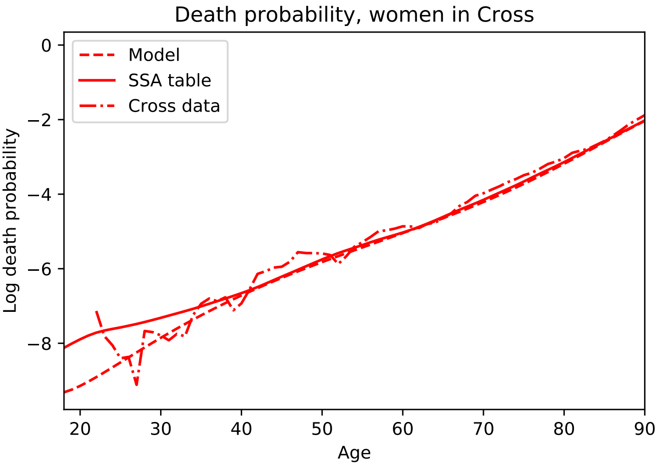
Naive SRHS transitions for cross-data women: 10 years



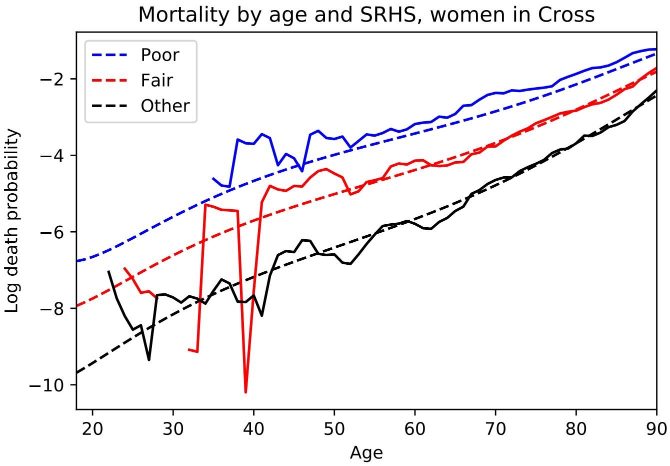
Estimated parameters: Cross-data women (mortality)

Param	Description	Cross
θ_0	Mortality probit: constant term	3.622
		(0.353)
θ_{x1}	Mortality probit: linear coefficient on health	0.141
		(4.96e-3)
θ_{x2}	Mortality probit: quadratic coefficient on health	-3.88e-3
		(4.66e-4)
θ_{j1}	Mortality probit: linear coefficient on age	-5.70e-2
		(1.74e-2)
θ_{j2}	Mortality probit: quadratic coefficient on age	8.86e-4
		(2.75e-4)
θ_{j3}	Mortality probit: cubic coefficient on age	-6.85e-6
		(1.41e-6)
θ_{xj}	Mortality probit: coefficient on age$\times$health	-2.90e-5
		(2.69e-5)

Model fit: Mortality by age for cross-data women



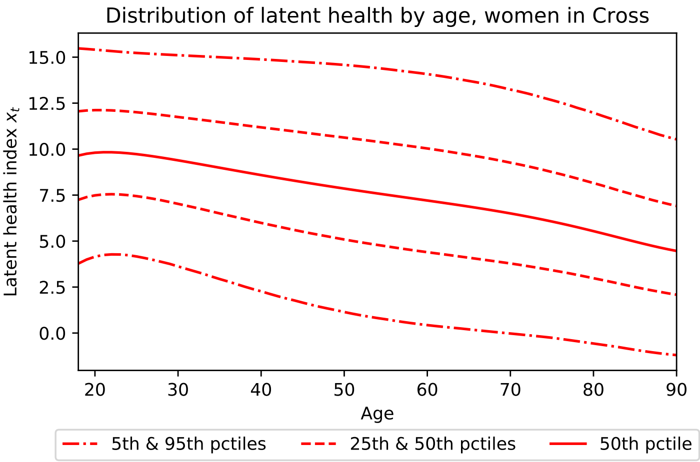
Model fit: Mortality by age-SRHS for cross-data women



Estimated parameters: Cross-data women (health)

Param	Description	Cross
β_0	Expected health: constant term	21.369
		(1.317)
β_{j1}	Expected health: linear coefficient on age	-0.752
		(9.78e-2)
β_{j2}	Expected health: quadratic coefficient on age	9.25e-3
		(2.62e-3)
β_{j3}	Expected health: cubic coefficient on age	2.98e-5
		(3.37e-5)
β_{j4}	Expected health: quartic coefficient on age	-9.16e-7
		(1.86e-7)
μ_0	Mean of latent health at model start	9.875
		(0.110)
σ_0	Standard deviation of latent health at model start	3.563
		(6.36e-2)

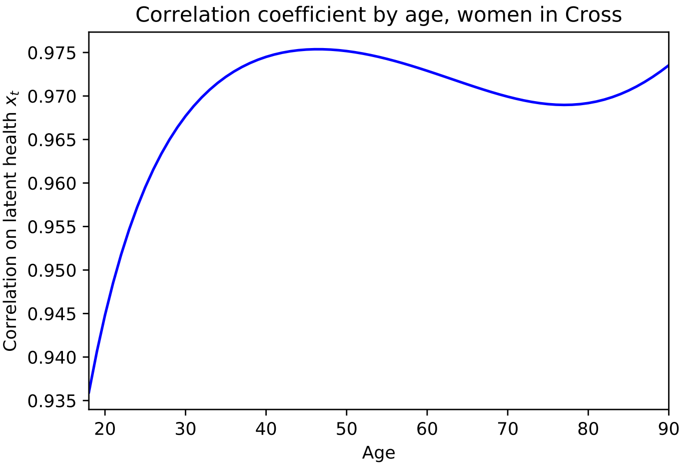
Estimated model: Distribution of latent health (cross-data women)



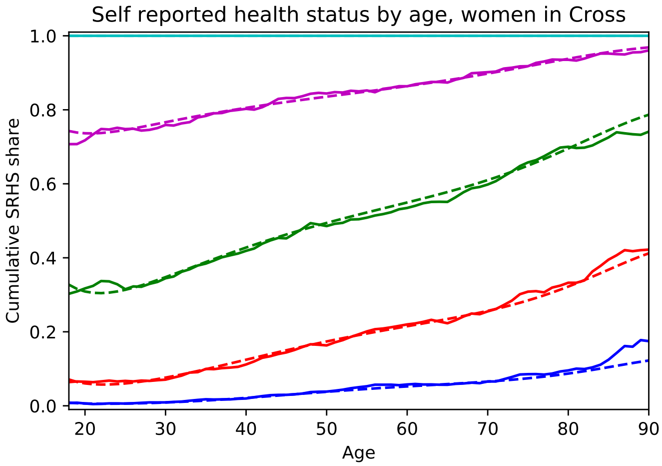
Estimated parameters: Cross-data women (correlation and SRHS)

Param	Description	Cross
γ_0	Correlation factor: constant term	0.337 (0.186)
γ_{j1}	Correlation factor: linear coefficient on age	0.178 (1.21e-2)
γ_{j2}	Correlation factor: quadratic coefficient on age	-3.08e-3 (2.41e-4)
γ_{j3}	Correlation factor: cubic coefficient on age	1.67e-5 (1.52e-6)
α_1	SRHS: Linear coefficient on latent health	0.480 (5.23e-3)
χ_2	SRHS: Cut b/w reporting "fair" and "good"	1.805 (9.61e-3)
χ_3	SRHS: Cut b/w reporting "good" and "very good"	3.814 (1.41e-2)
χ_4	SRHS: Cut b/w reporting "very good" and "excellent"	5.974 (1.95e-2)

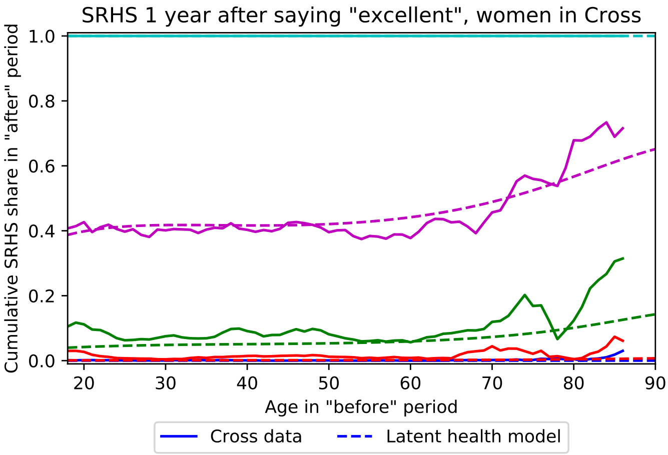
Estimated model: Latent health serial correlation (cross-dataset women)



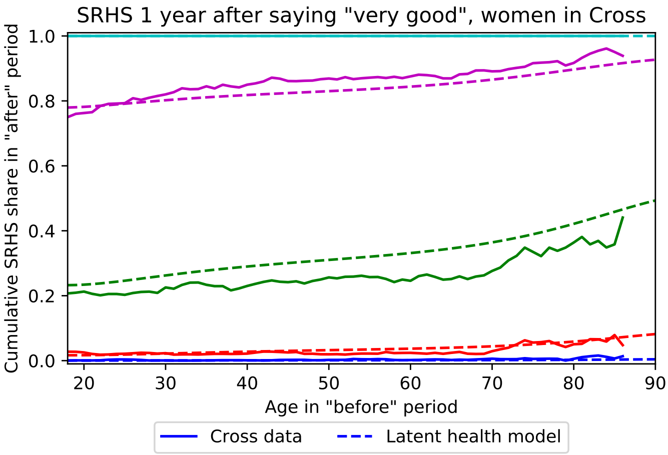
Model fit: SRHS by age for cross-data women



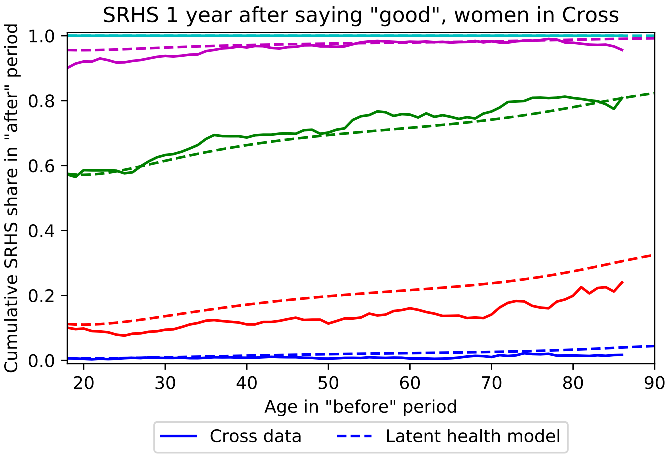
Model fit: SRHS transitions for cross-data women: 1 year



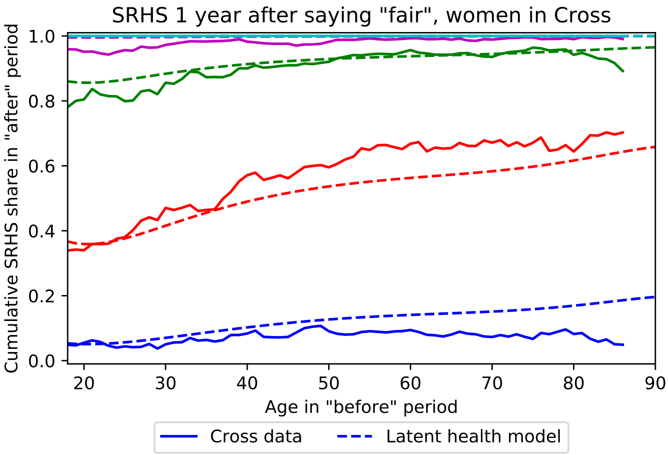
Model fit: SRHS transitions for cross-data women: 1 year



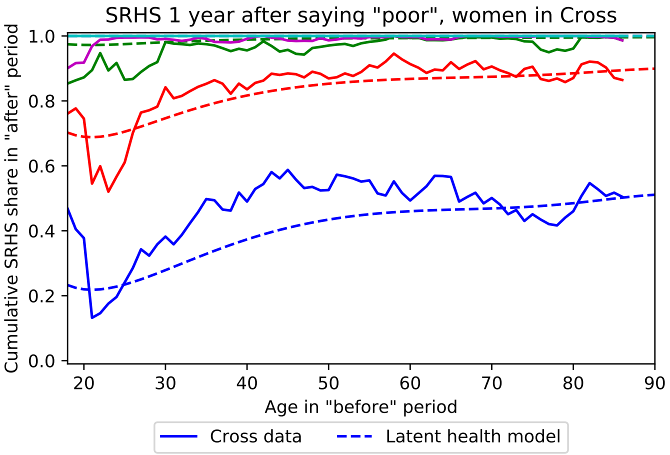
Model fit:e SRHS transitions for cross-data women: 1 year



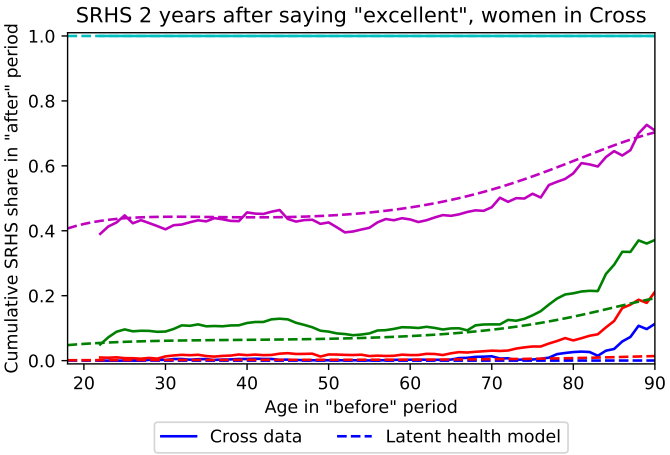
Model fit: SRHS transitions for cross-data women: 1 year



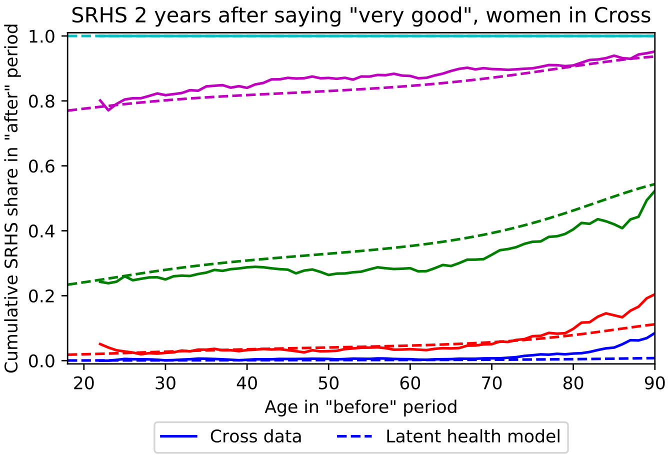
Model fit: SRHS transitions for cross-data women: 1 year



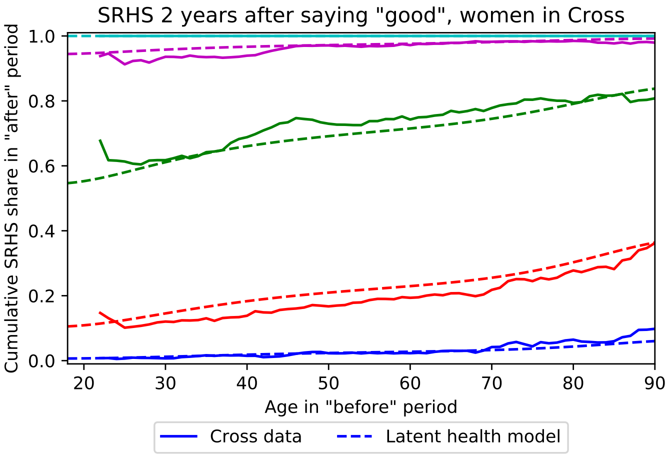
Model fit: SRHS transitions for cross-data women: 2 years



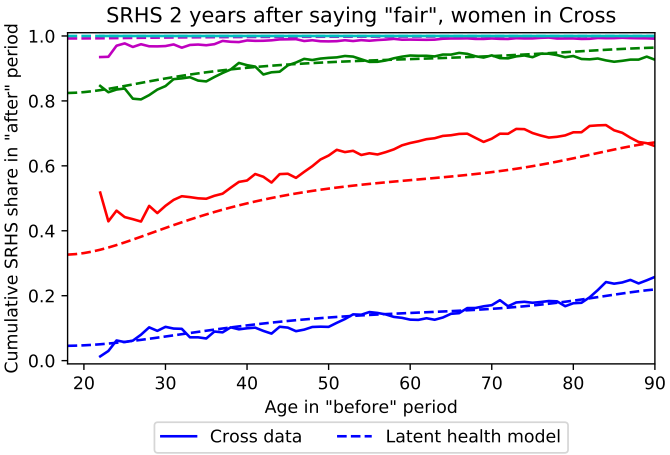
Model fit: SRHS transitions for cross-data women: 2 years



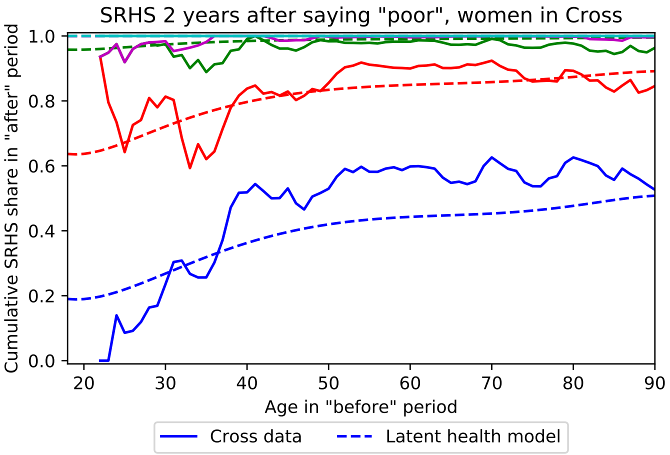
Model fit: SRHS transitions for cross-data women: 2 years



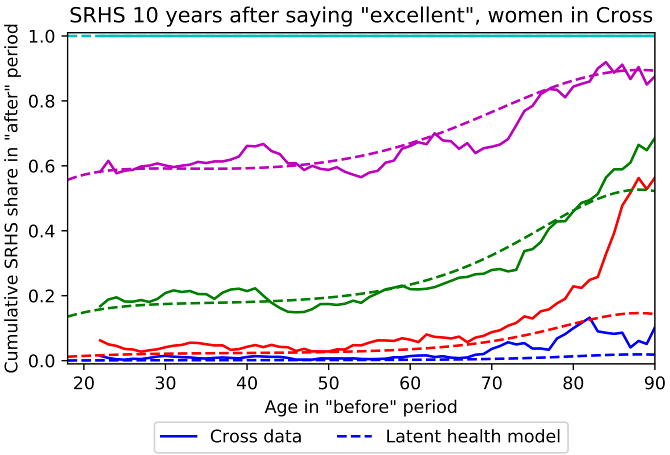
Model fit: SRHS transitions for cross-data women: 2 years



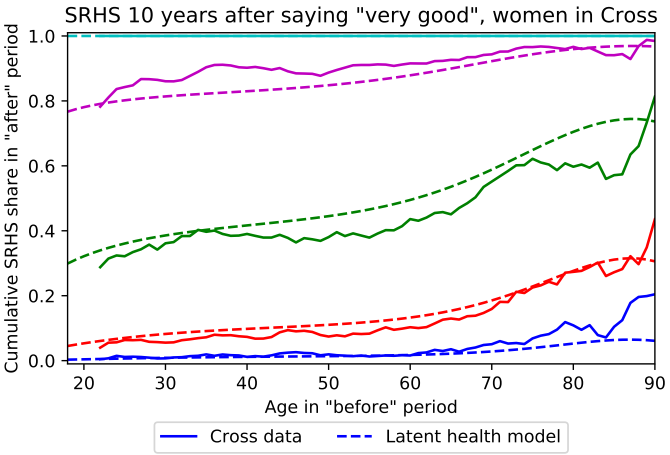
Model fit: SRHS transitions for cross-data women: 2 years



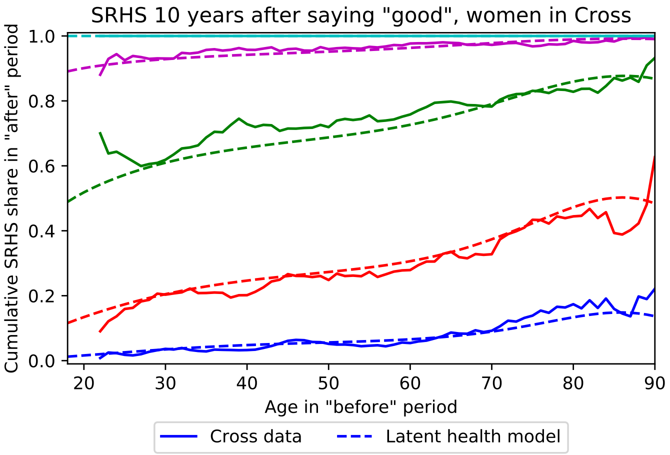
Model fit: SRHS transitions for cross-data women: 10 yrs



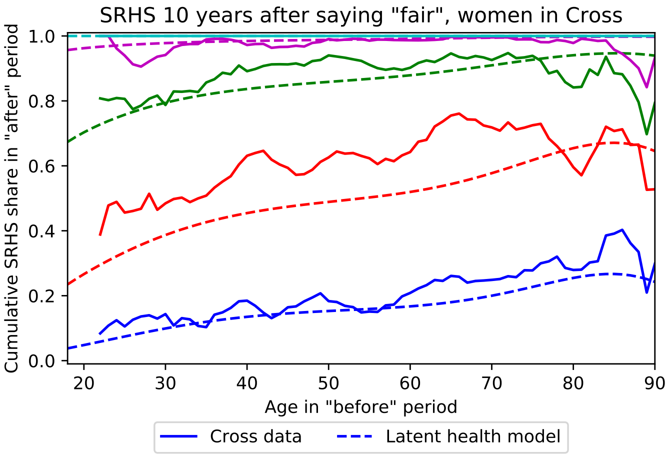
Model fit: SRHS transitions for cross-data women: 10 yrs



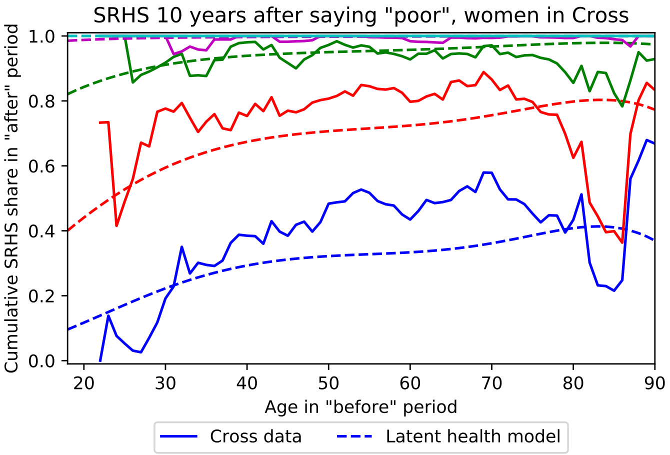
Model fit: SRHS transitions for cross-data women: 10 yrs



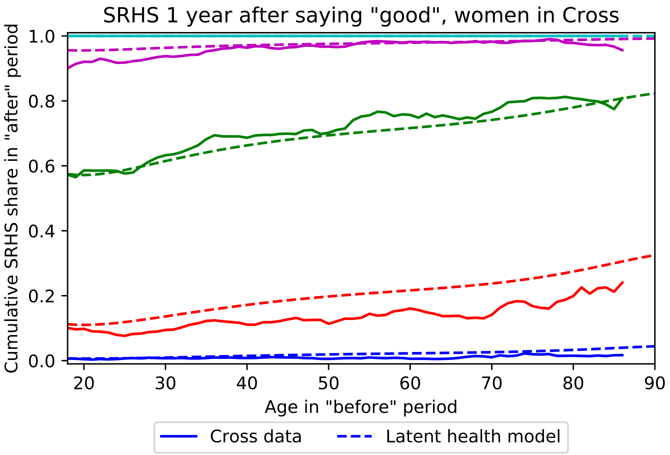
Model fit: SRHS transitions for cross-data women: 10 yrs



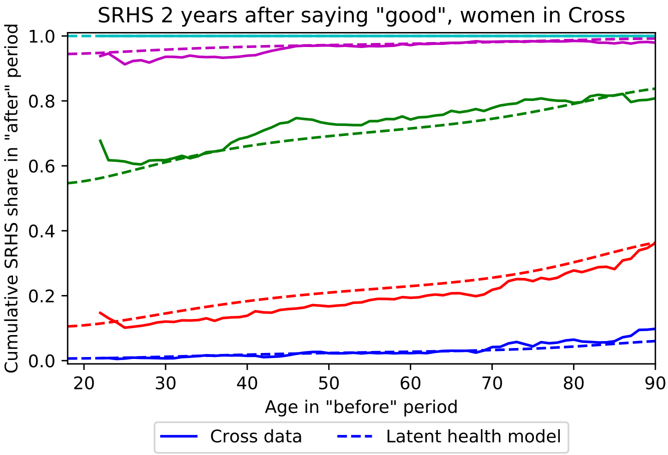
Model fit: SRHS transitions for cross-data women: 10 yrs



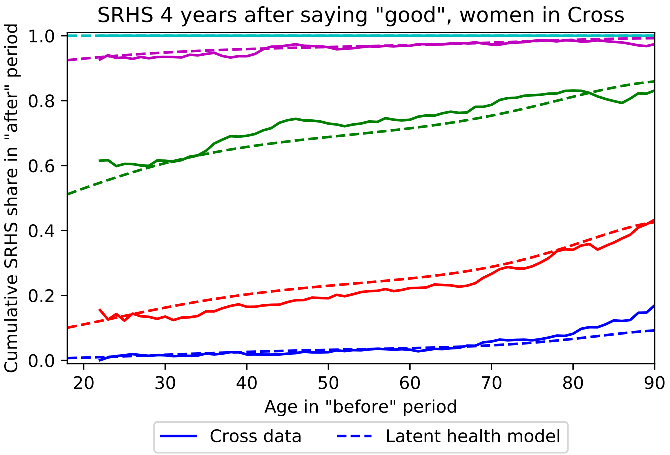
Model fit: SRHS transitions for cross-data women: 1 year



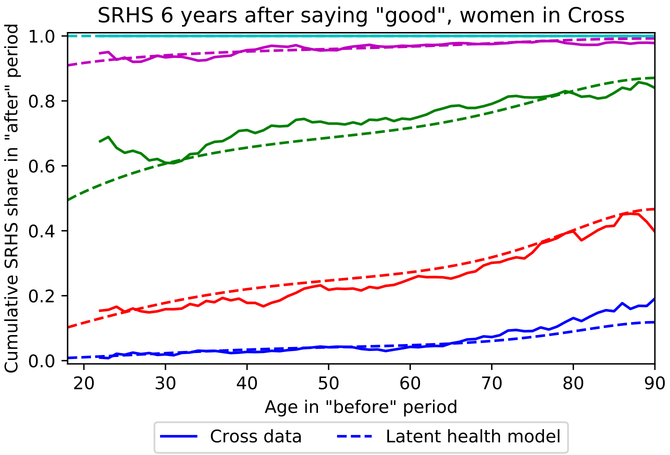
Model fit: SRHS transitions for cross-data women: 2 years



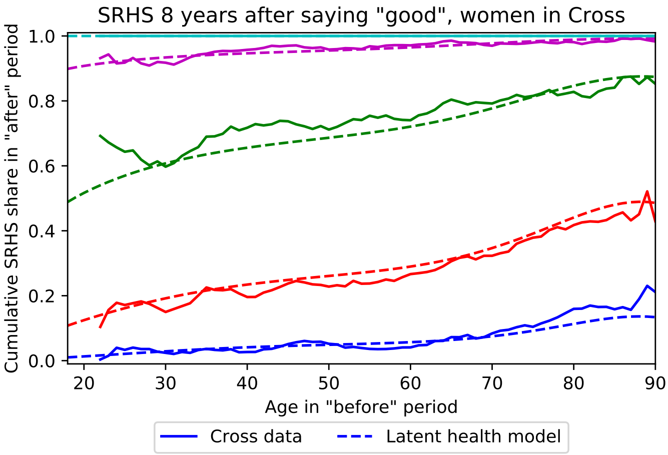
Model fit: SRHS transitions for cross-data women: 4 years



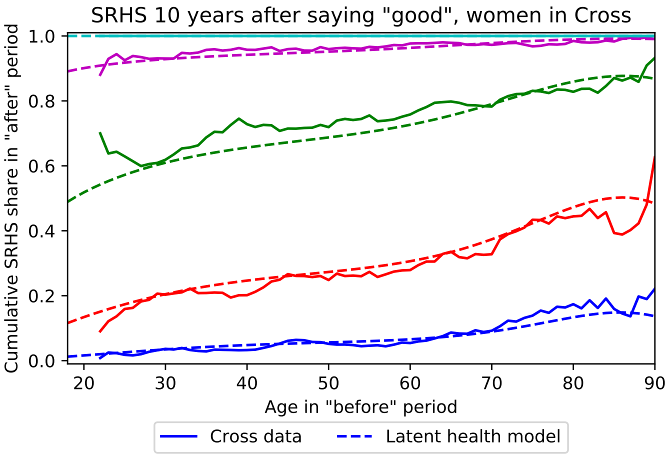
Model fit: SRHS transitions for cross-data women: 6 years



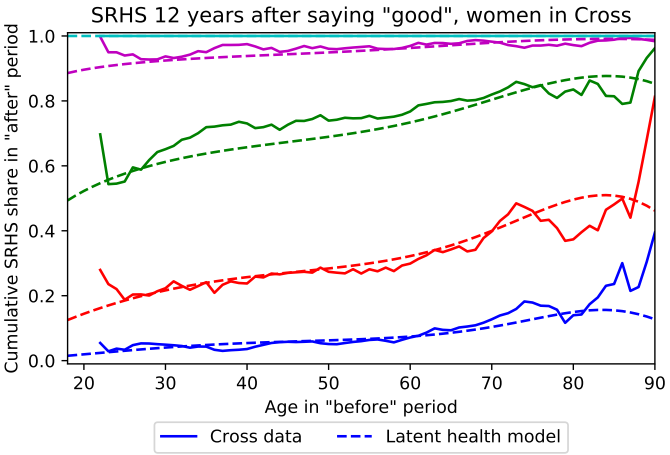
Model fit: SRHS transitions for cross-data women: 8 years



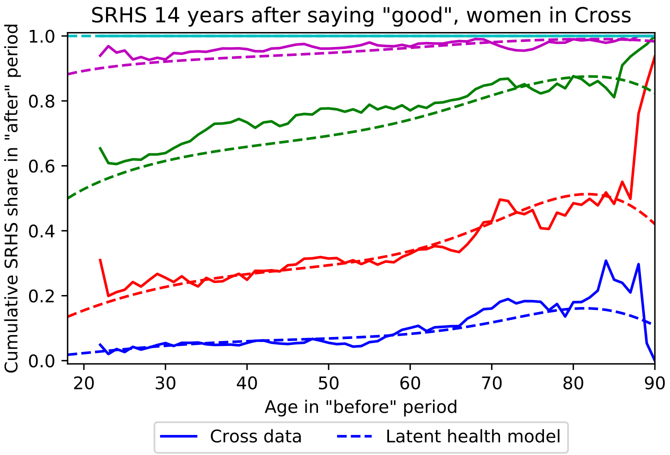
Model fit: SRHS transitions for cross-data women: 10 yrs



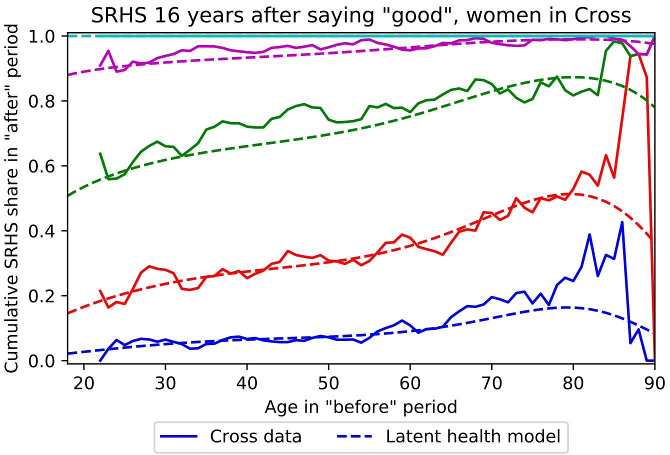
Model fit: SRHS transitions for cross-data women: 12 yrs



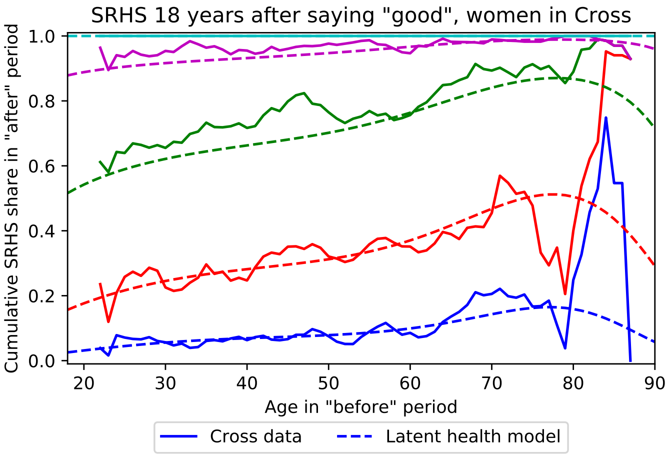
Model fit: SRHS transitions for cross-data women: 14 yrs



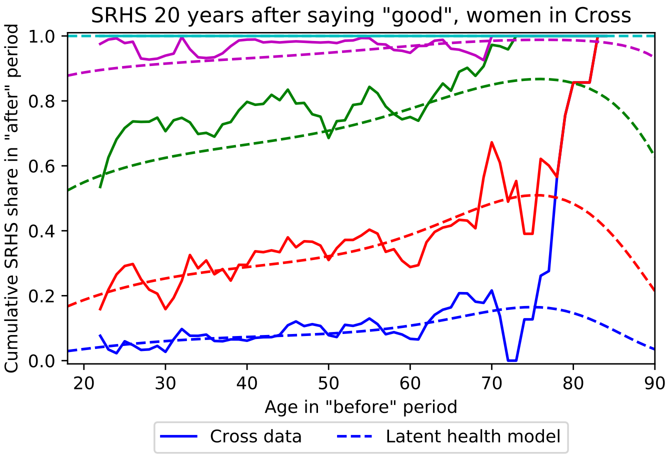
Model fit: SRHS transitions for cross-data women: 16 yrs



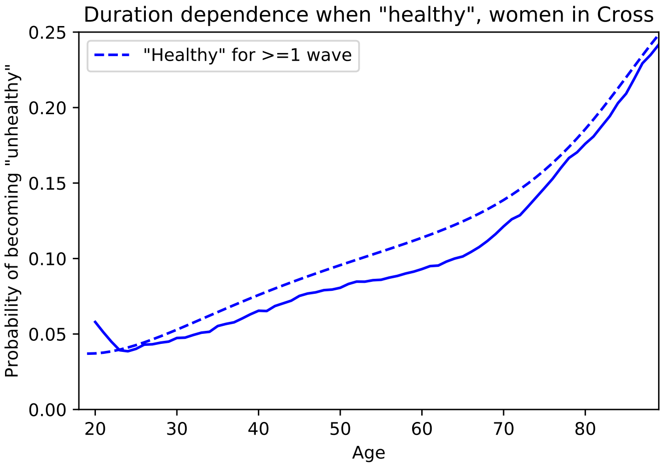
Model fit: SRHS transitions for cross-data women: 18 yrs



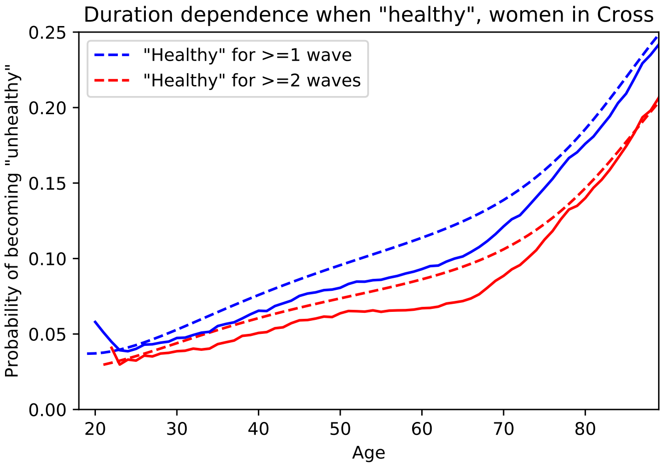
Model fit: SRHS transitions for cross-data women: 20 yrs



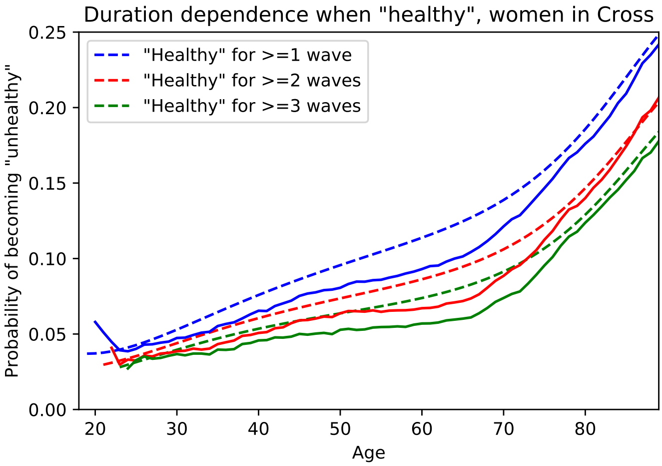
Model fit: Duration dependence, “healthy” to “unhealthy”



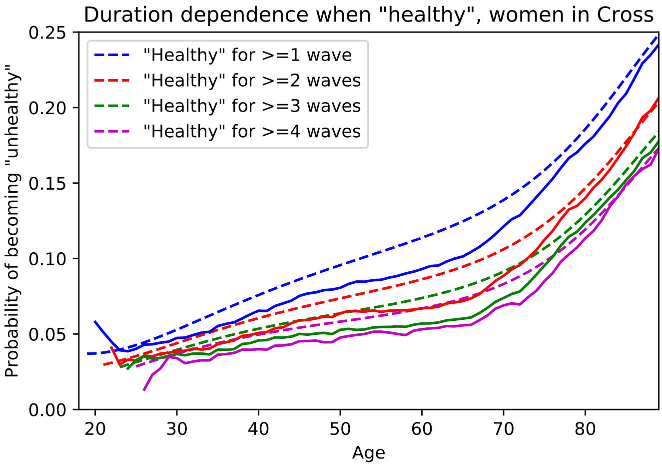
Model fit: Duration dependence, “healthy” to “unhealthy”



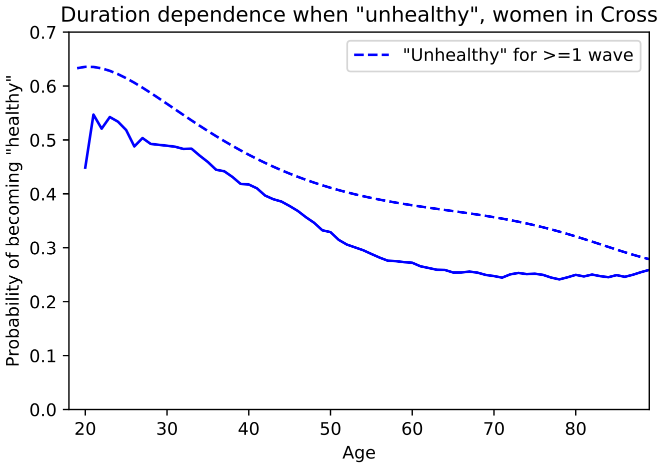
Model fit: Duration dependence, “healthy” to “unhealthy”



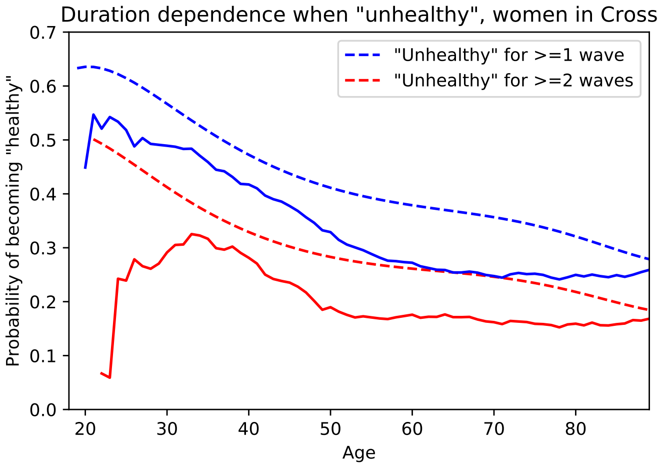
Model fit: Duration dependence, “healthy” to “unhealthy”



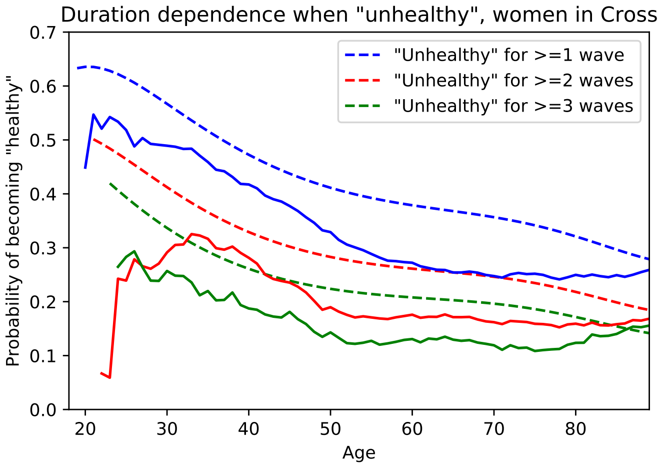
Model fit: Duration dependence, “unhealthy” to “healthy”



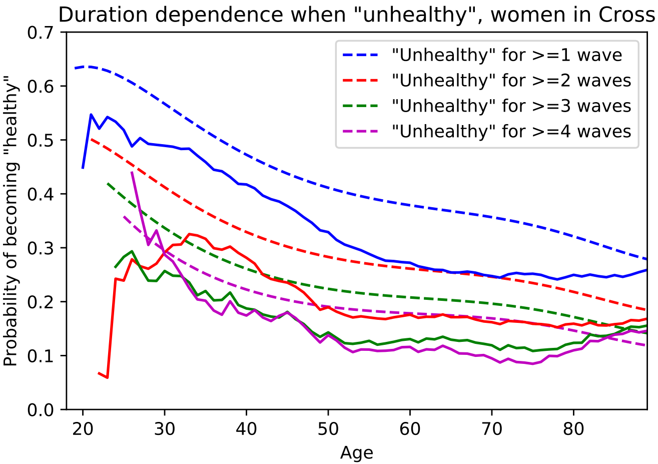
Model fit: Duration dependence, “unhealthy” to “healthy”



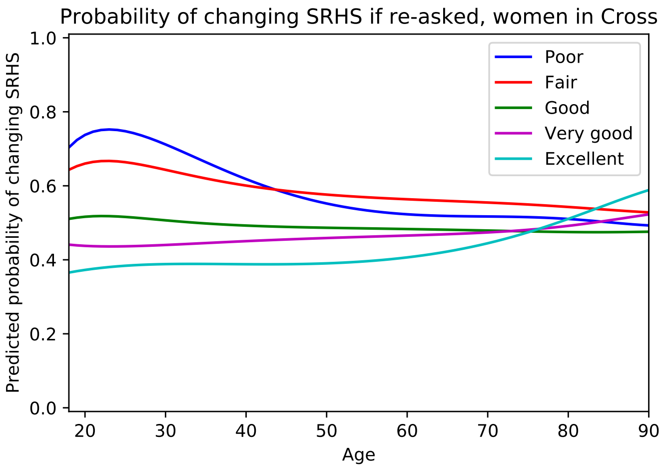
Model fit: Duration dependence, “unhealthy” to “healthy”



Model fit: Duration dependence, “unhealthy” to “healthy”

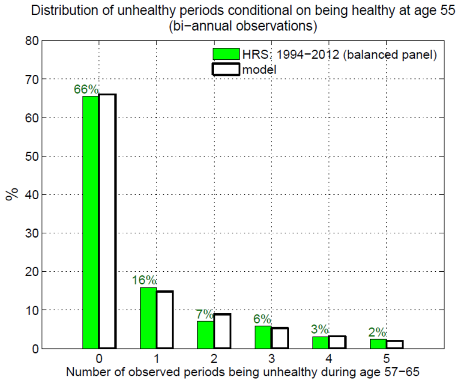


Estimated model: Changing SRHS if asked twice (cross-data women)

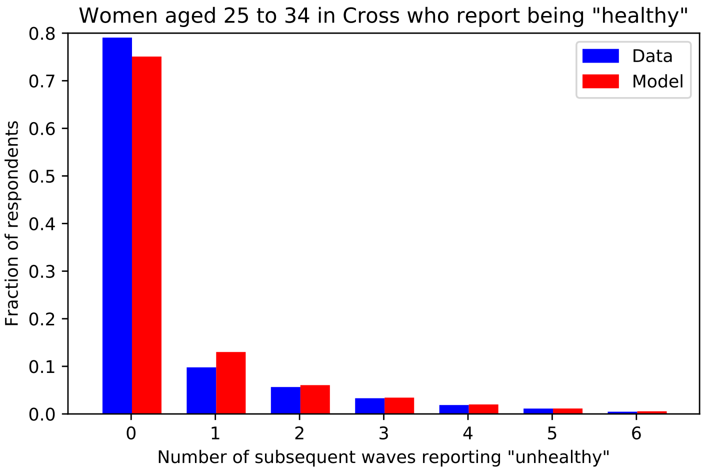


Model fit: Within-person distribution of “unhealthy” periods

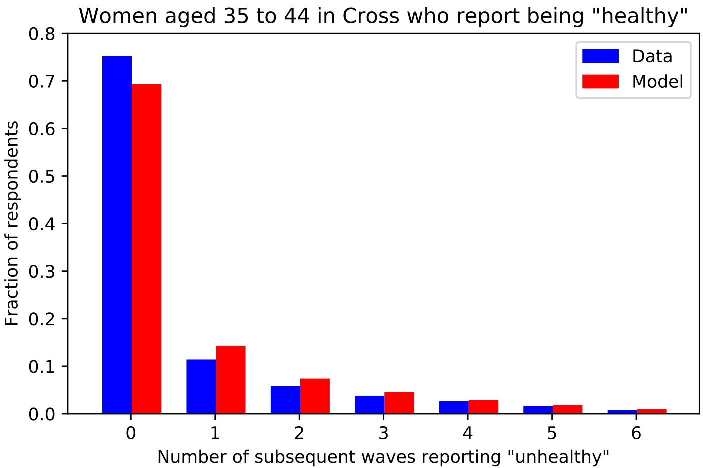
- DeNardi et al (2018) show that their duration dependence / unobserved heterogeneity model fits the distribution of “unhealthy” periods over next 5 waves
- Can the latent health model do that as well?



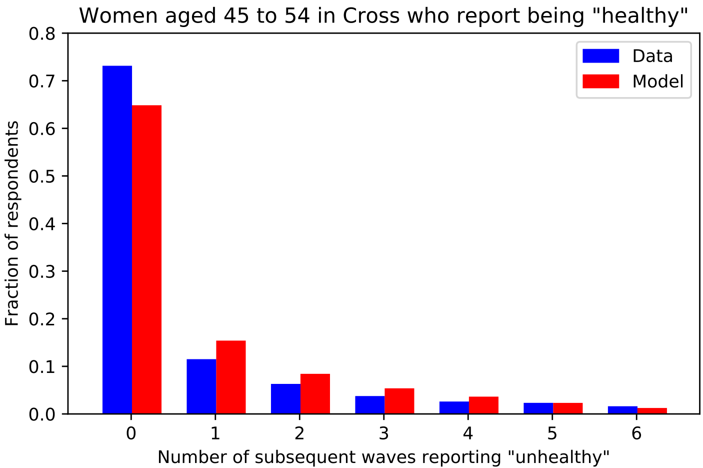
Model fit: Freqency of reporting “unhealthy” (cross-data women)



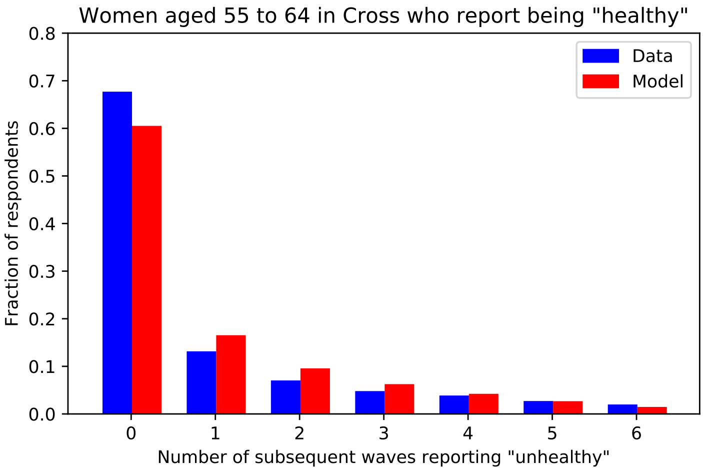
Model fit: Freqency of reporting "unhealthy" (cross-data women)



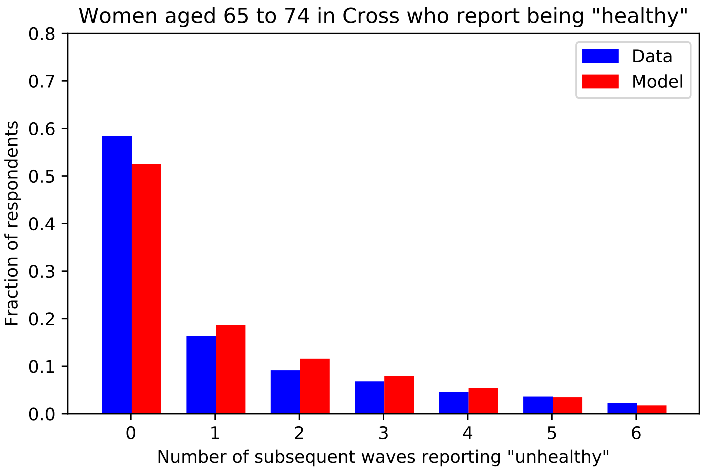
Model fit: Freqency of reporting “unhealthy” (cross-data women)



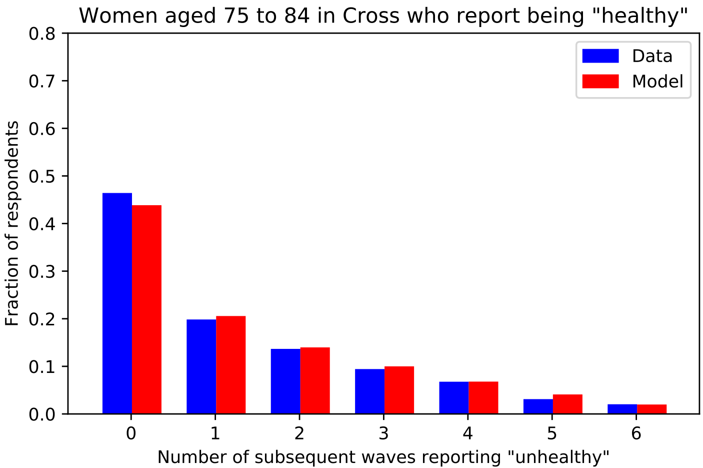
Model fit: Freqency of reporting “unhealthy” (cross-data women)



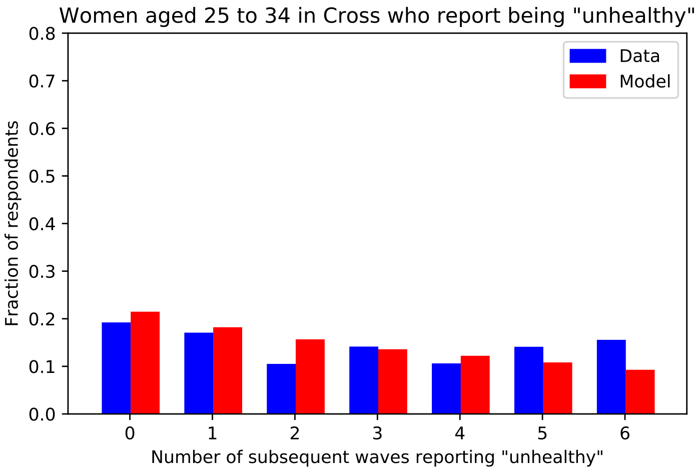
Model fit: Freqency of reporting "unhealthy" (cross-data women)



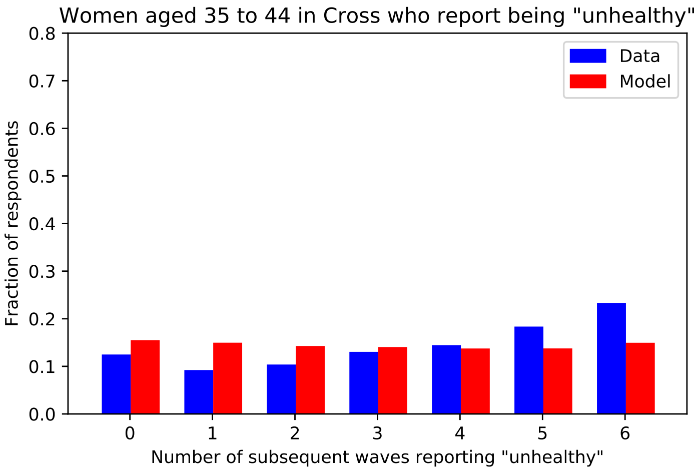
Model fit: Freqency of reporting “unhealthy” (cross-data women)



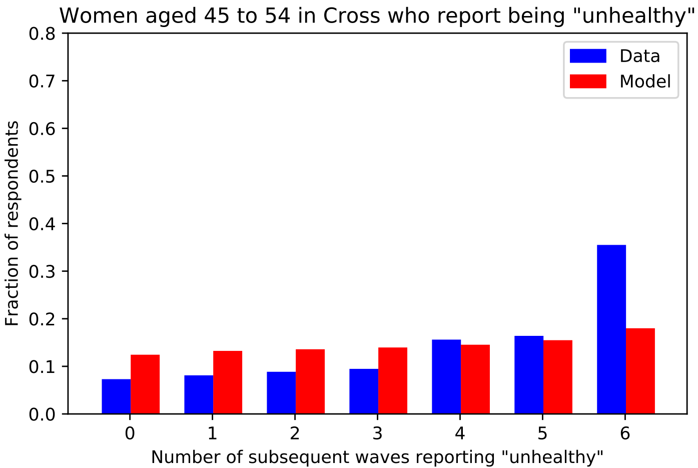
Model fit: Freqency of reporting “unhealthy” (cross-data women)



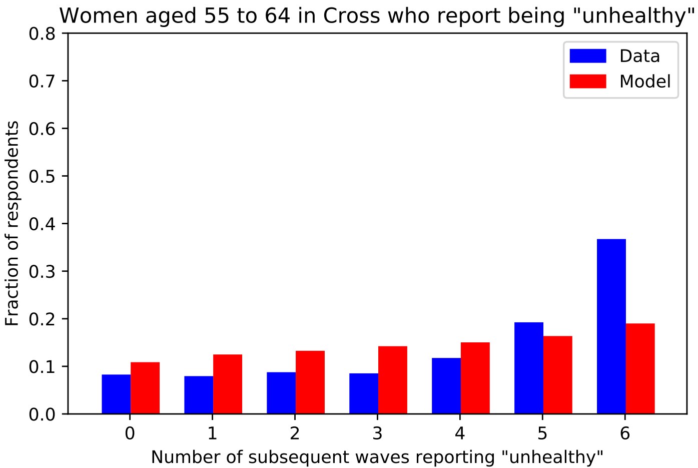
Model fit: Freqency of reporting “unhealthy” (cross-data women)



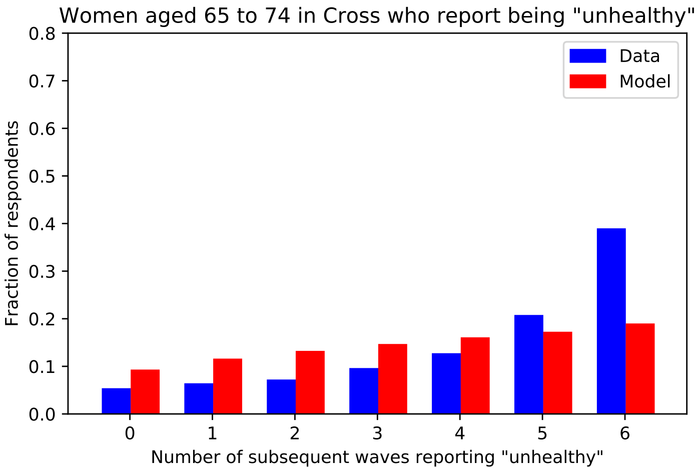
Model fit: Freqency of reporting “unhealthy” (cross-data women)



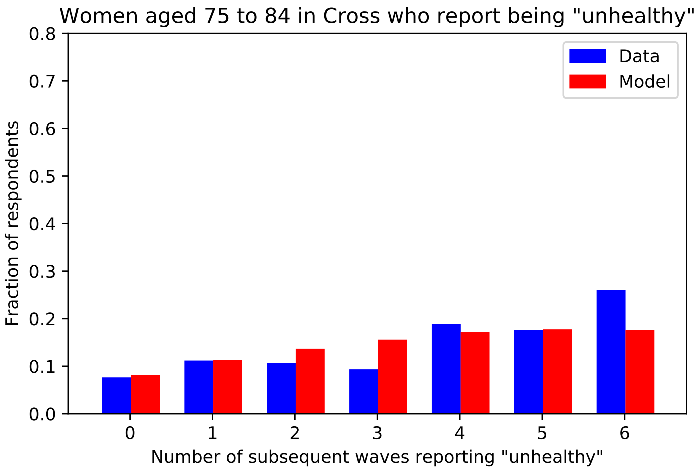
Model fit: Freqency of reporting “unhealthy” (cross-data women)



Model fit: Freqency of reporting “unhealthy” (cross-data women)



Model fit: Freqency of reporting “unhealthy” (cross-data women)



EXTENSIONS

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- No: Similar results with SRHS or constructed index from multiple measures. Self-justification bias is offset by attenuation bias!

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- And want representation of health that structural models can handle!
- Need multiple measures to be able to address subjective SRHS, skewed shocks, or second latent factor, so let's start there

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- Extent to which pain interferes with normal work activities
- Clinical measures: hand grip strength, walking speed, lung capacity

Latent health model with single measure (SRHS)

Baseline latent health model:

$$x_0 \sim N(\mu_0, \sigma_0^2). \tag{1}$$

$$\text{Prob}(h_{t+1} = 0) = 1 - \Phi(f(j_t, x_t)). \tag{2}$$

$$x_{t+1} = \rho_j x_t + (1 - \rho_j) g(j_t) + \epsilon_{t+1}, \qquad \epsilon_{t+1} \sim \Phi. \tag{3}$$

$$h_t^* = \alpha_0 + \alpha_1 x_t + \eta_t, \qquad \eta_t \sim \Phi, \tag{4}$$

$$h_t = 1 + \sum_{k=1}^{K-1} \mathbf{1}(h_t^* \geq \chi_k).$$

Latent health model with multiple measures (1/2)

Latent health model with multiple independent measures:

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$$m^*_{\ell t} = \alpha_{\ell 0} + \alpha_{\ell 1} x_t + \eta_{\ell t}, \qquad \eta_{\ell t} \sim \Phi, \tag{4}$$

$$m_{\ell t} = 1 + \sum_{k=1}^{K_\ell - 1} \mathbf{1}(m^*_t \geq \chi_{k\ell}), \qquad \ell \in \{0, \cdots, L\}, \qquad h_t \equiv m_{0t}.$$

Latent health model with multiple measures (2/2)

- Each wave, observe multiple categorical measures of latent health
- Measure 0 is set aside for SRHS (and mortality)
- Location assumption: $\chi_{1\ell} = 0 \ \forall \ell$, but only $\alpha_{00} = 0$

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- Adding another measure **should not** affect estimates of other α coefficients
- Obvious violation: Second latent factor (omitted variable bias)
- My MLE code is already set up to estimate such a model, and appropriate datasets have been constructed...
- ...but I don't have a specification or results I'd like to share today

Adding other model extensions

- With multiple measures, have **more objective** observations of health
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- ...or whether they're "pessimists" who have different labeling standard
- And can test whether normality of latent health shocks is well supported
- Nothing in core MLE code has to change to add these features!
- **Label heterogeneity:** Discretized x_t vector would include "type"; change precomputed report probability matrix, tile transition probabilities
- **Skewed health shocks:** Just change precomputed transition probability array for x_t, probably use mixed normal (impose mean 0, stdev 1)

Latent health model: Adding SRHS labeling heterogeneity

Latent health model with "labeling shifter" for SRHS:

$$x_0 \sim N(\mu_0, \sigma_0^2), \qquad \delta \sim \text{Discrete}. \tag{1}$$

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- All hail Moore's law!