

Health Inequality and Pain

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Complexity and Health (George Kaplan et al.)**

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Plan of the Presentation (I)

- health inequalities – what are the issues
 - whenever measured, inequalities are there
 - when are health inequalities just or unjust ? – depends on idea of counterfactuals = “what if?”
 - \Rightarrow how to represent and characterize empirically the “web of causality” in adequate detail
- disjoint approaches to “unjust” health inequalities
 - A. moral philosophy – *discusses sources* of health inequality; but generally no references to data
 - B. standard empirical methods – *describes* “the gradient” statistically; looks for correlates; but generally no moral reasoning, just “gradient bad”

Plan of the Presentation (II)

- new: HealthPaths microsimulation model approach
 - bring together moral reasoning (the “sources” of health inequality) and “causal” empirical analysis
 - use highly detailed statistical analysis of longitudinal data
 - ❖ that from the start is designed to be
 - tightly coupled with a microsimulation model of the estimated “web of causality”
 - use empirical results in order to simulate counterfactuals – specifically “*what if*” **unjust sources of health inequality were removed?**
 - (and try out data visualization for “explainability”)

Health Inequalities – Various Definitions

- “inequalities in health” = Gini coefficient of (age-standardized) ages at death (LeGrand, 1987)
 - note: focus on **univariate** distribution, nothing on SES
- “Equity has long been considered an important goal in the health sector. Yet inequalities between the poor and the better-off persist.” (World Bank, 2007)
 - note: inequity = inequality; and presumes inequity is entirely about the SES gradient; a **bivariate** relationship
- health equity = “the absence of systematic disparities in health ... between social groups who have different levels of underlying social advantage/disadvantage” (Braveman & Gruskin)
 - note: “social groups” \Rightarrow categorical variable, and bivariate

“Beware of the Mean”

- well-intentioned population health interventions that improve population health overall may have the unintended consequence of increasing health inequality, e.g.
 - smoking cessation campaigns
 - asthma management information to patients

(since better educated are more likely to change behaviour based on the public health / health care information provided)

Moral Philosophy and Unjust Health Inequalities – Various Definitions

- health inequality is unjust (= unfair = inequitable) if due to factors related to unequal opportunities, or amenable to policy interventions (Asada, Hausman)
- “health inequalities .. plausibly attributed to freely undertaken personal choices are fair” (Deaton)
 - skydiving? but what about Médecins Sans Frontières?
- what really matters is overall well-being, where health is only one component; health inequalities are only unjust if they are not compensated in other domains of well-being (Deaton)
 - OK, focus only on interventions unlikely to have noticeable effects on other domains of well-being

Measuring Health Inequalities

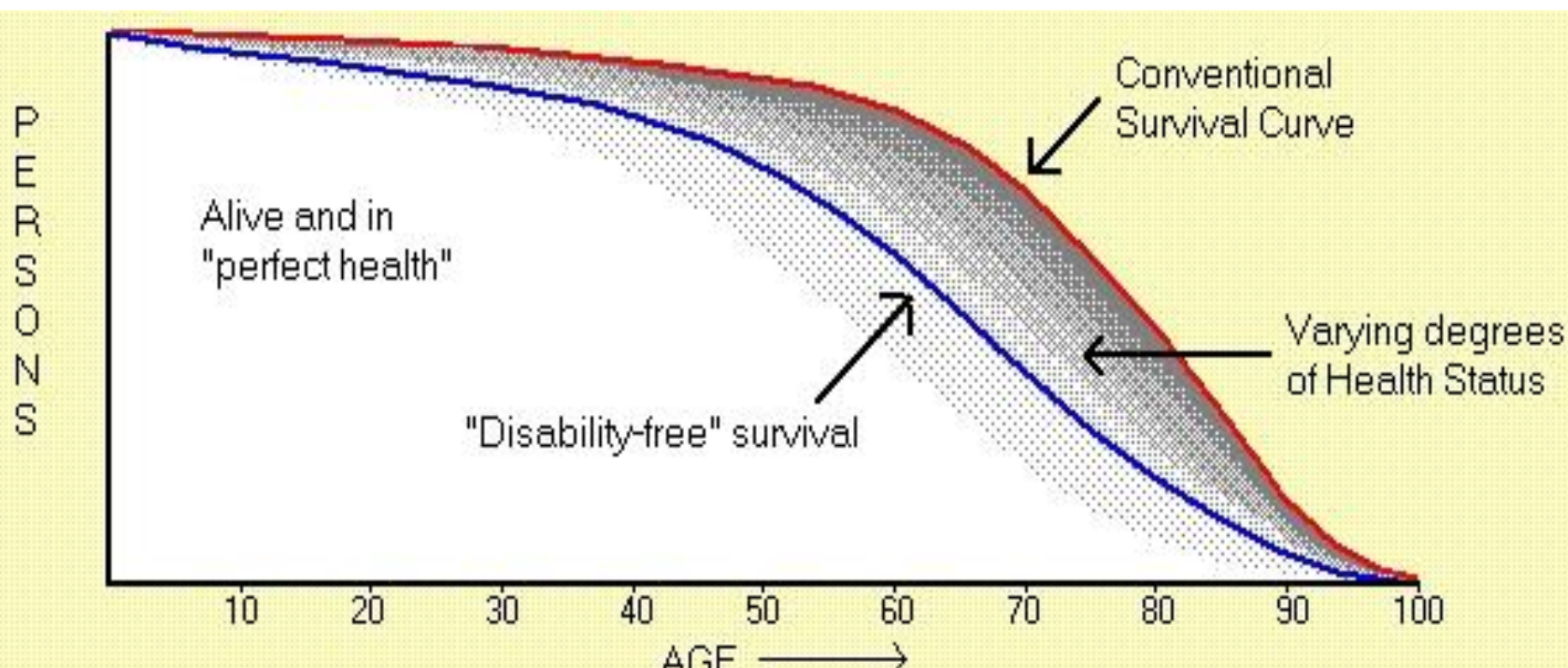
- important to distinguish univariate and bivariate approaches
 - major argument between Murray and Marmot
 - e.g. Wolfson and Rowe (2001); Asada (2013)
- most prevalent – bivariate distributions, especially SES gradients
- rather unusual – univariate distribution
 - e.g. Legrand (1987, 1989)
- but if we want to compare SES with other (un)just sources of health inequalities, we need a metric or approach that is independent of SES

Health Inequalities – Conventional Approaches to Observation

- health status by socio-economic status (e.g. income, education) or other factors (e.g. gender, race, geography)
- mortality rates by small area average income
- these approaches are essentially cross-sectional, and treat health status while living separately from mortality
- this analysis
 - brings together health status and mortality
 - looks at full life-cycles, not age groups

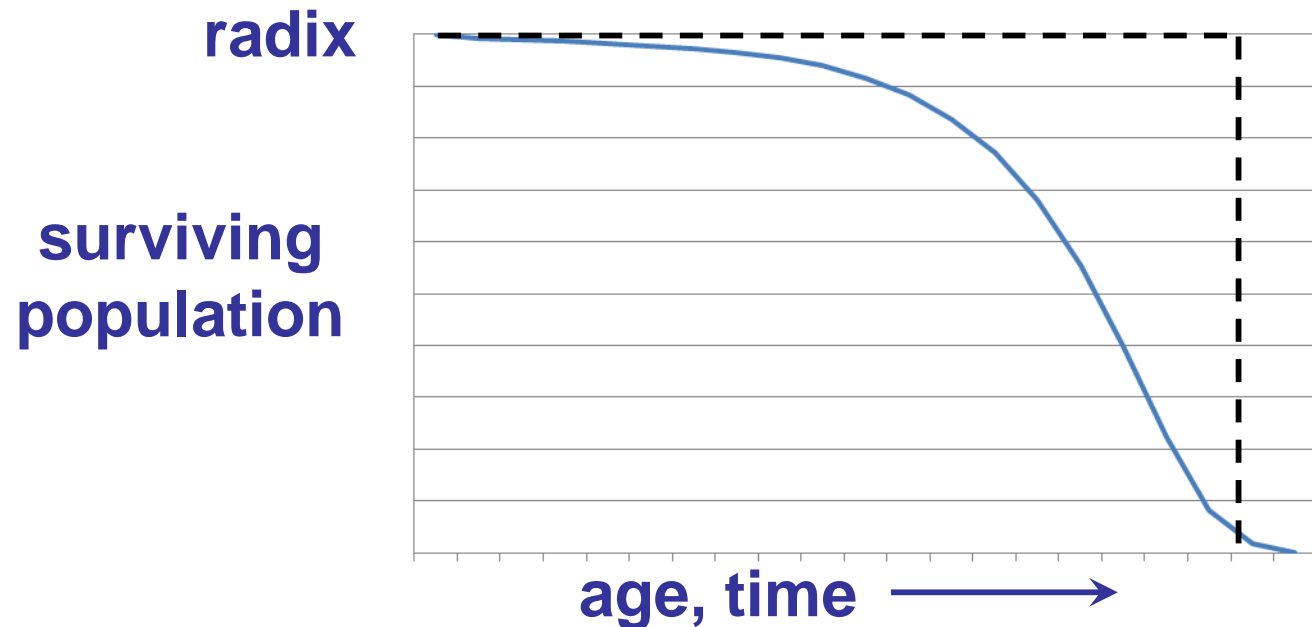
Health Inequalities – Of What?

- focus will be on Life Expectancy (LE)
= area under survival curve
- and Health-Adjusted Life Expectancy (HALE)
= “weighted” area under survival curve, where “weights” are levels of individual health status, ranging between zero (dead) and one (fully healthy)



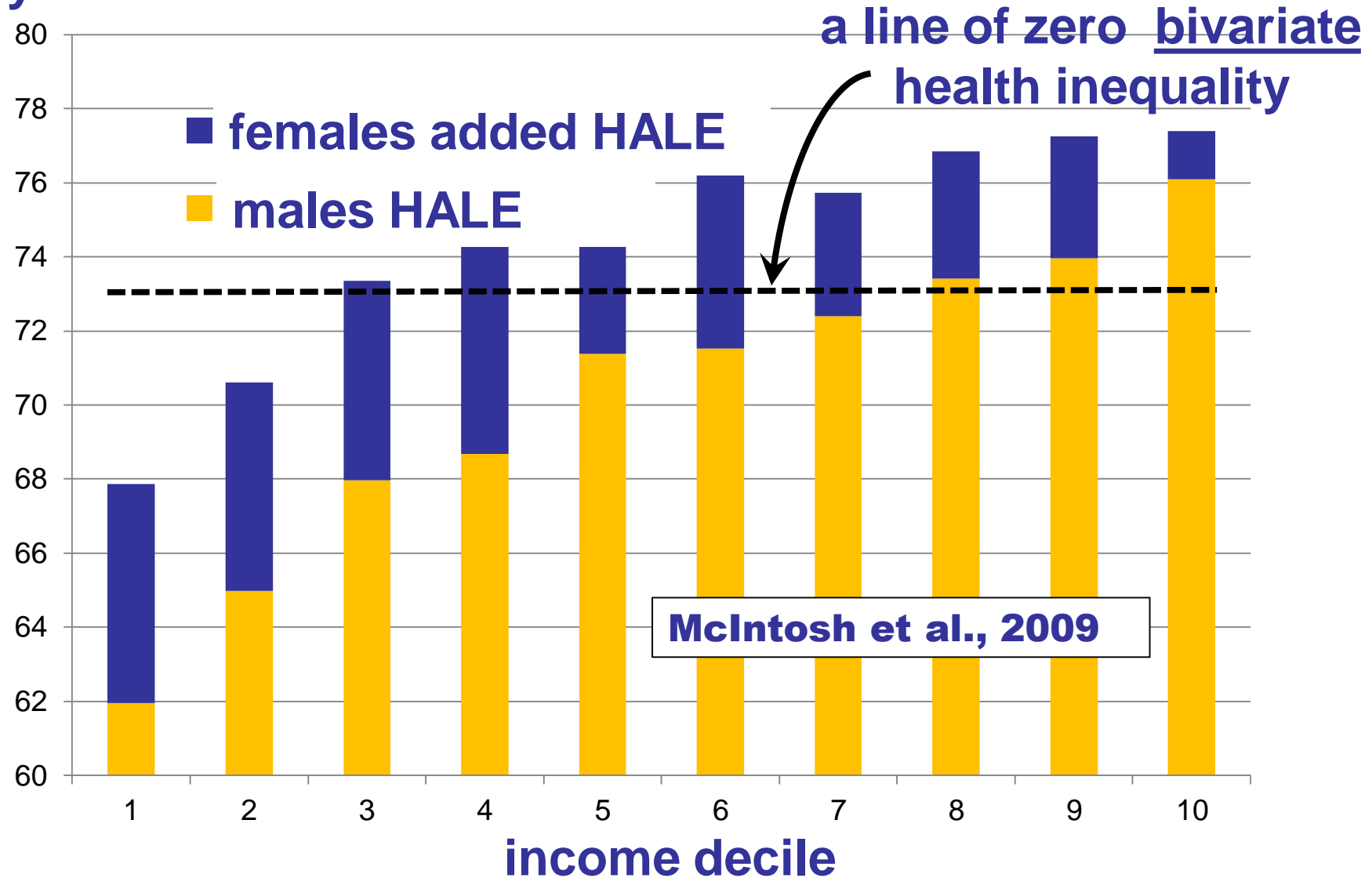
Conventional Survival Curve and Univariate Health inequality

- dispersion in ages at death \equiv inequality
- zero inequality \equiv rectangular survival curve, i.e. everyone dies at exactly the same age



Conventional SES Gradient in HALE Showing Bivariate Health Inequality

years



Bridging Moral Philosophy and Empirical Analysis

- posit a “web of causality” (Krieger)
 - select health measures and widely-accepted causal factors / “health determinants”
- use statistical estimation to quantify all the pathways in the “web of causality”
 - recognize complexity of multiple interactions and their essential co-evolution
- embed statistical results in a tightly coupled microsimulation model – HealthPaths
- simulate health inequality “what if” = cause-deleted impacts of removing ameliorable causes
 - far more sophisticated than conventional biomedical / life table cause-deleted life expectancy, e.g. cancer

HealthPaths – Main Ideas / Innovations

- focus on determinants of HALE = health-adjusted life expectancy (a complex “dependent variable”)
- beyond conventional population attributable fractions, and categorical attribution (as in GBD)
- build on heterogeneous individual / micro-level life course / longitudinal trajectories
- focus on functional health (vs diseases, biomarkers – recall Bob Evans, “disease as epiphenomenon”)
- include co-morbidity & competing risks explicitly
- represent “casual web” as multiple co-evolving dynamic relationships

HealthPaths Construction and Use

- use longitudinal Statistics Canada's National Population Health Survey + mortality follow-up
- estimate multiple co-evolving individual health and health-related dynamic relationships, generalizing concept of risk function
- incorporate into HealthPaths microsimulation model
- use counter-factual simulations to assess relative importance to Δ HALE of major health determinants,
- use a *visual/graphical metric* for health inequalities
- estimate and display impacts of three ***ameliorable*** \Rightarrow ***unjust*** sources of health inequalities on ***univariate*** distributions of LE and HALE

Statistics Canada's National Population Health Survey (NPHS)

- started in 1994; interviews every 2 years; includes institutionalized, mortality follow-up
- n = ~20,000 initially; in 2008 ~14,000
- all responses self-report (+ mortality)
- mostly conventional health survey content, e.g. socio-demographics, chronic disease check list, major risk factors, health care utilization
- plus some content more exploratory content, e.g. Antonovsky's Sense of Coherence, Pearlin / Schoolers' Sense of Mastery, McMaster Health Utilities Index (HUI)

Bootstrap Weights

- NPHS has a complex sample design
 - so bootstrap weights were provided to enable straightforward and correct variance estimation
 - for each bootstrap weight vector, ~40% of the weights are identically zero
- innovative use of bootstrap weights in HealthPaths:
 - estimation via cross-validation; minimizing out-of-sample prediction error; prevents over fitting (Rowe and Binder, 2008)
 - specification also bootstrapped using elastic net = mixture of ridge and lasso (Zhou and Hastie, 2005; Friedman, 2010) via glmnet
 - enabling simulations also to be bootstrapped

Focus of Analysis – Functional Health

- using NPHS Health Utility Index (HUI): a widely used generic index of functional health status.
 - 1 \Rightarrow full health
 - 0 \Rightarrow as good as dead
 - < 0 \Rightarrow worse than dead
- based on eight separately assessed attributes:
vision, hearing, speech, mobility, dexterity,
cognition, emotion, and pain
- aggregated into a summary numerical index
based on an empirical “weighting function”
- same as a generic (health-related) QALY

Estimation and Simulation Modeling Approach

- recall plan: focus on determinants of { HALE = complex object } \Rightarrow single equation approaches clearly inadequate \Rightarrow simulation essential
- specification of regression functional forms driven by overall analytical objectives
 - not print publication \Rightarrow no need for results to fit on one or two journal article pages
 - estimation process and simulation model design are simultaneous and tightly coupled
- since A can affect (change in) B (with lags), and B can affect (change in) A (also with lags), \Rightarrow need equations that reflect co-evolving processes

Risk Factors / Events and Health States Included

Ordinal Variables

- Vision
 - Hearing
 - Speech
 - Mobility
 - Dexterity
 - Emotion
 - Cognition
 - Pain
- } Functional Health summarized via HUI
- Income Decile
 - Leisure Activity
 - Daily Activity
 - Smoking

Binary Variables

- Employed this Year
- Family Member
- Institutional Resident
- High School Graduation
- Community College
- University Graduation
- Mortality

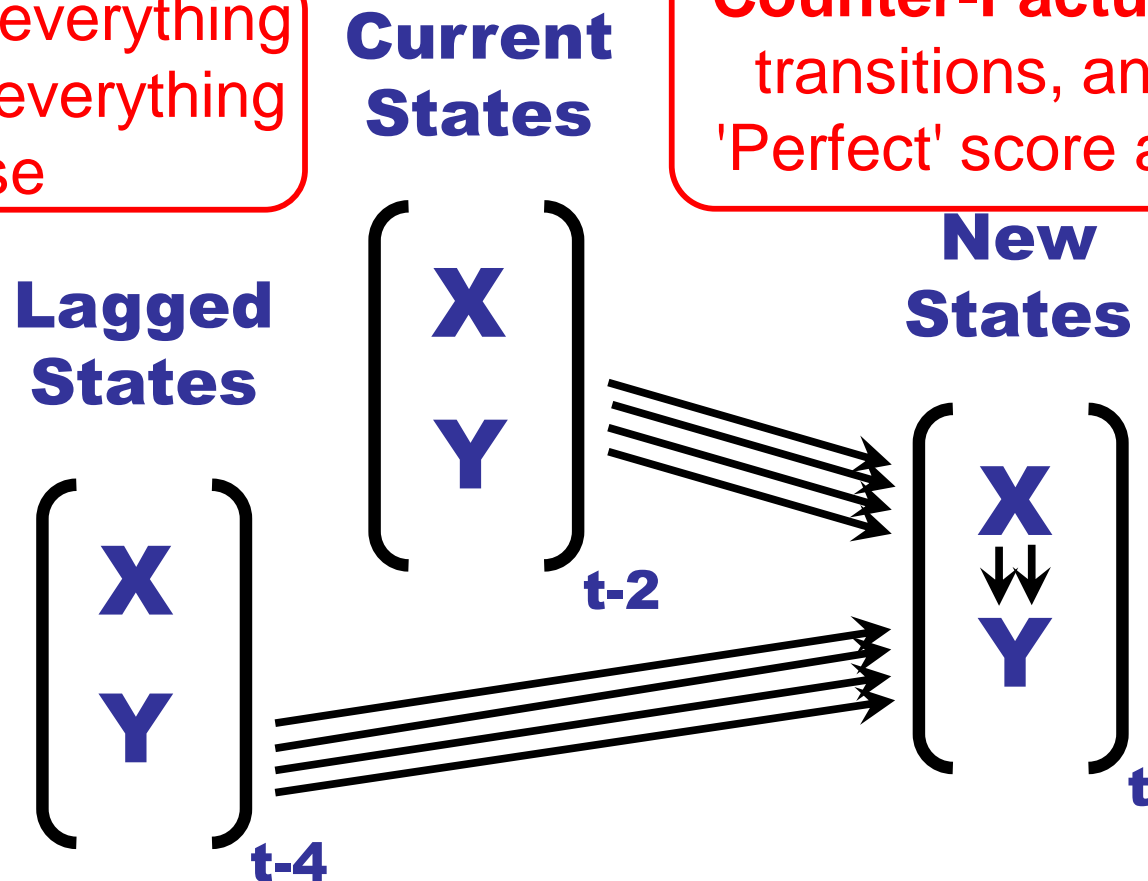
Quantitative Variables

- Body Mass Index
- Sense of Mastery
- Sense of Coherence
- Years of Daily Smoking

What-If Scenarios – Causal Attribution by Constructing Counter-Factuals

Baseline: everything influences everything else

Counter-Factual: over-ride transitions, and assign a 'Perfect' score at each step

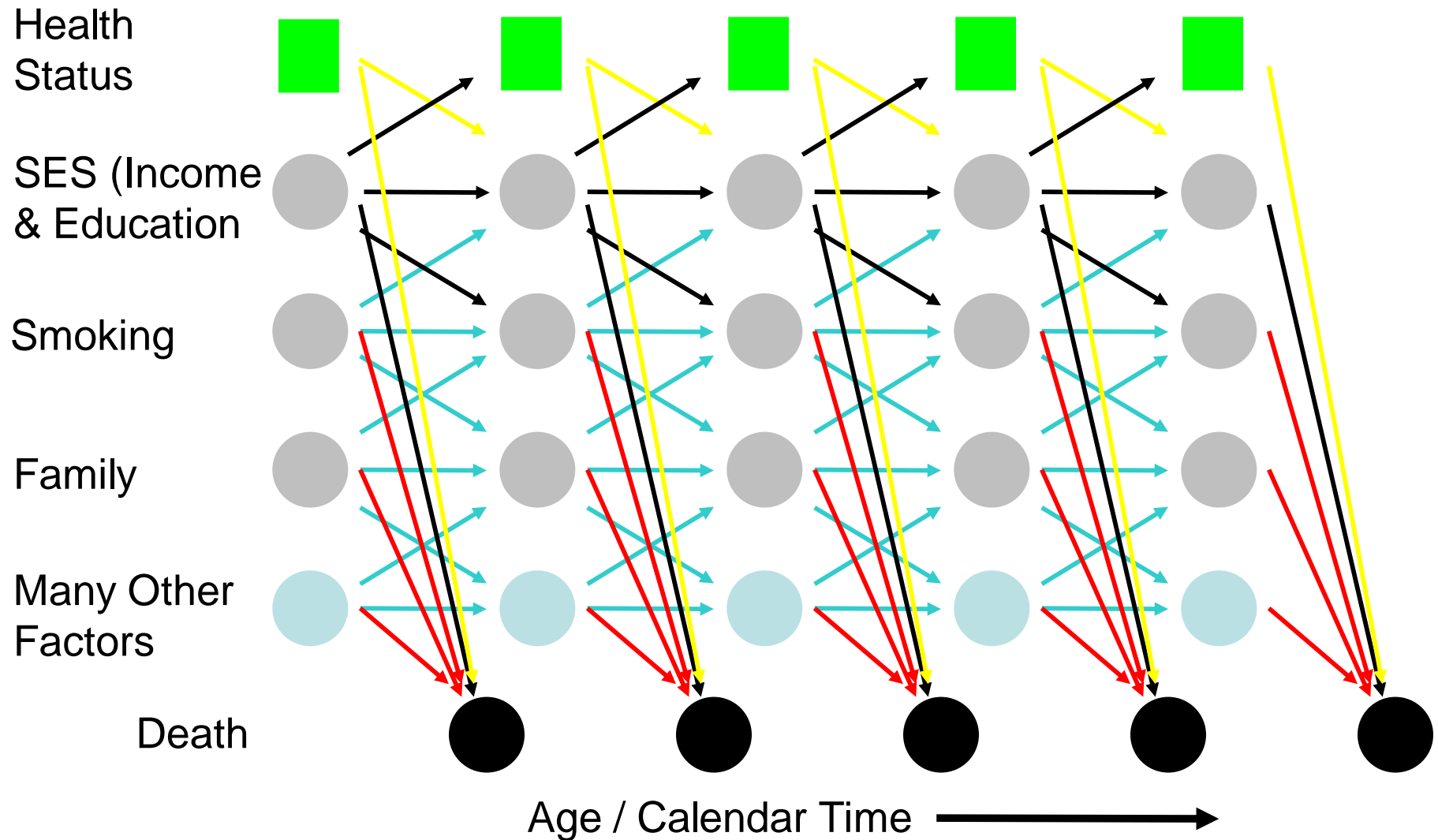


X 18 Binary & Ordinal Variables plus Mortality

Y 3 Quantitative Variables

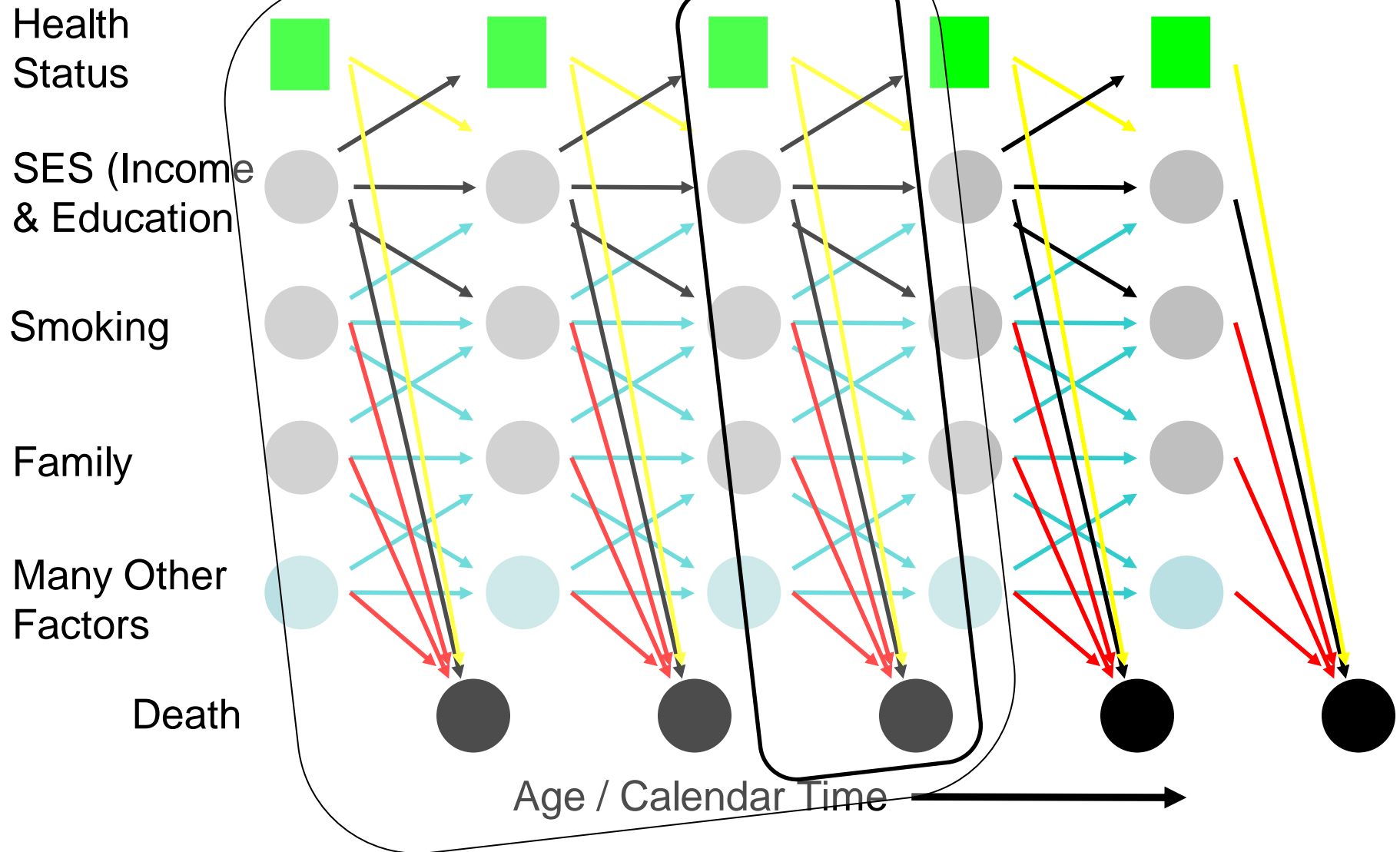
Step 1: Estimation Using NPHS, Multiple Equations for Co-Evolving and Mutually Interacting Factors

(n.b. not all possible arrows shown)



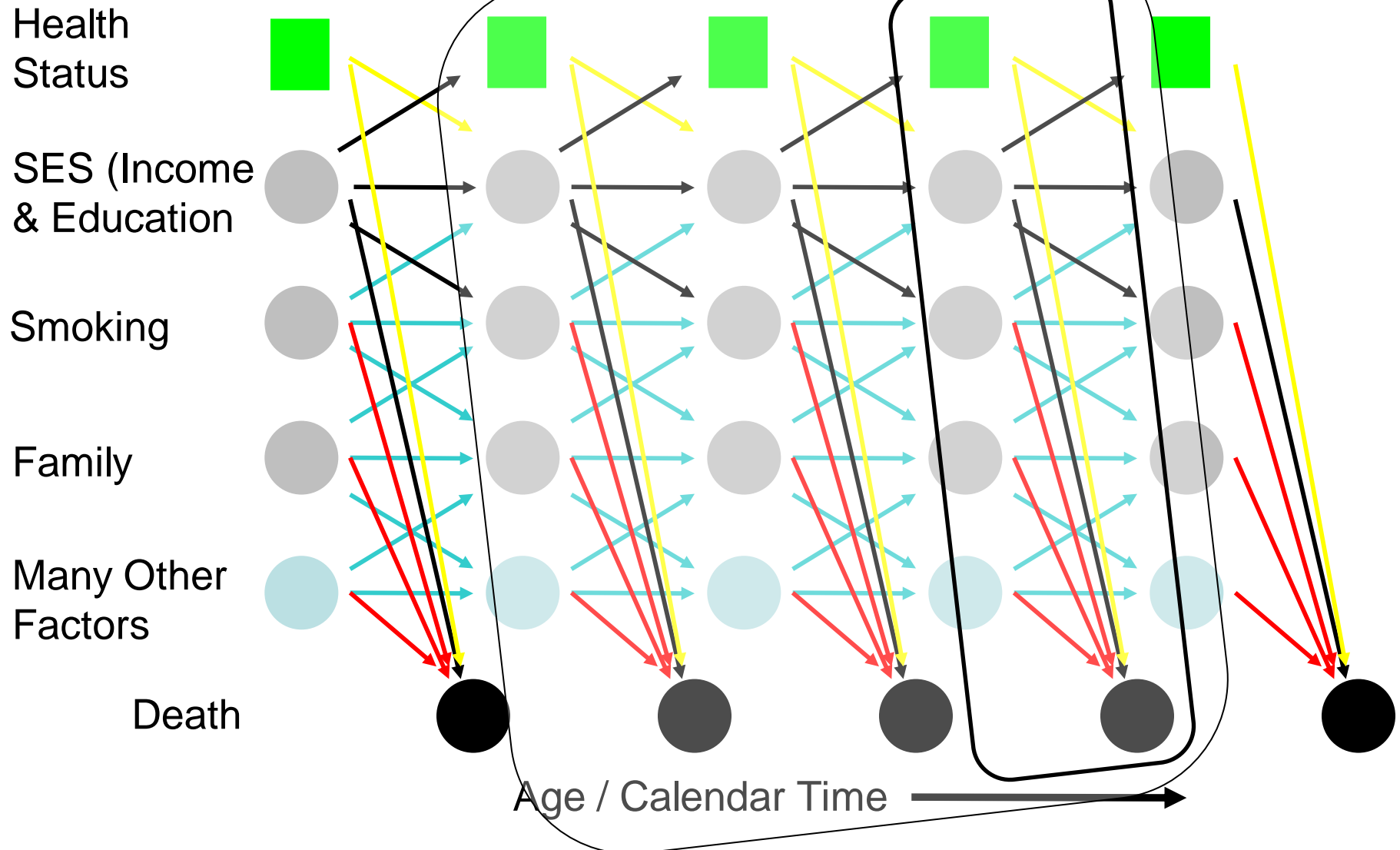
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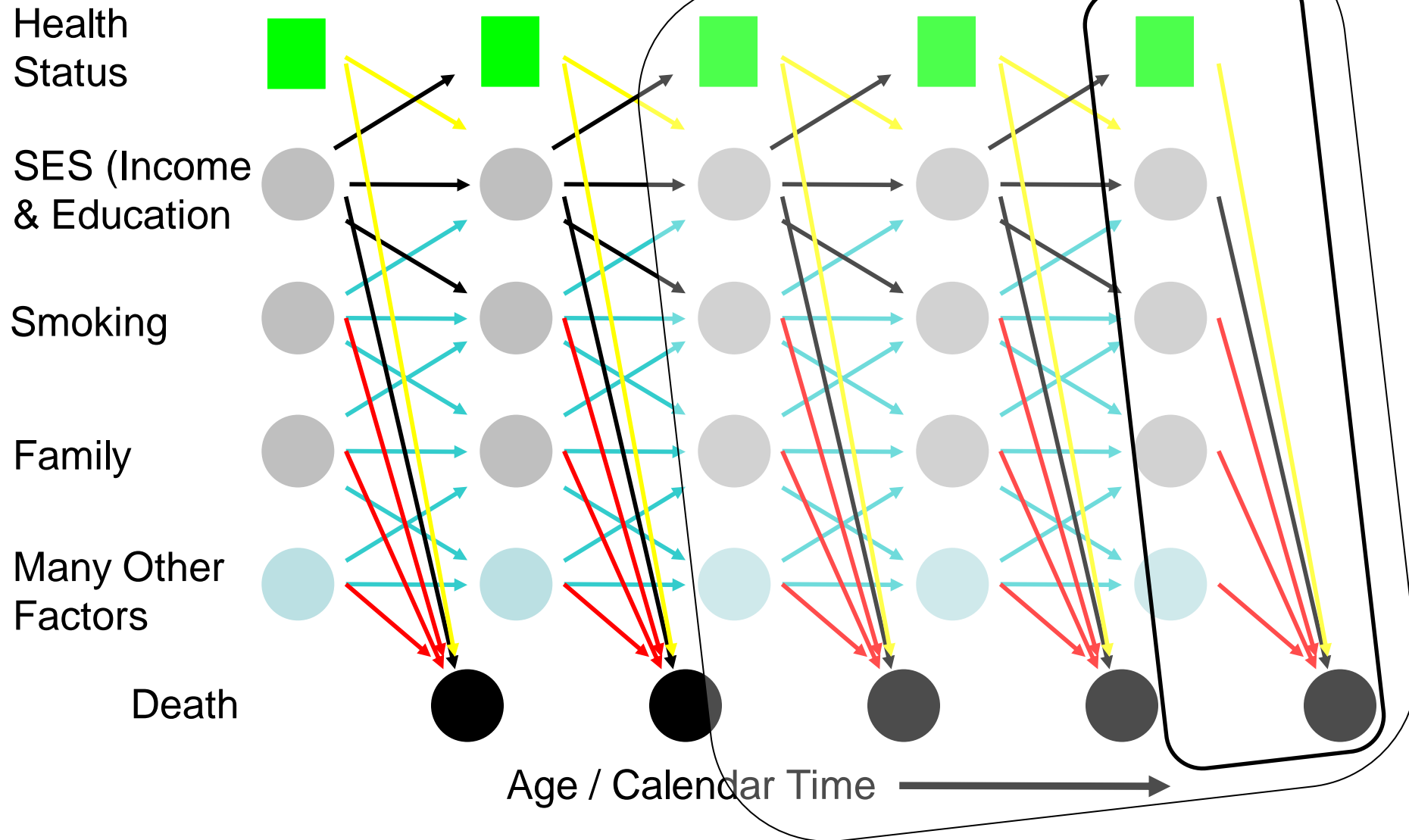
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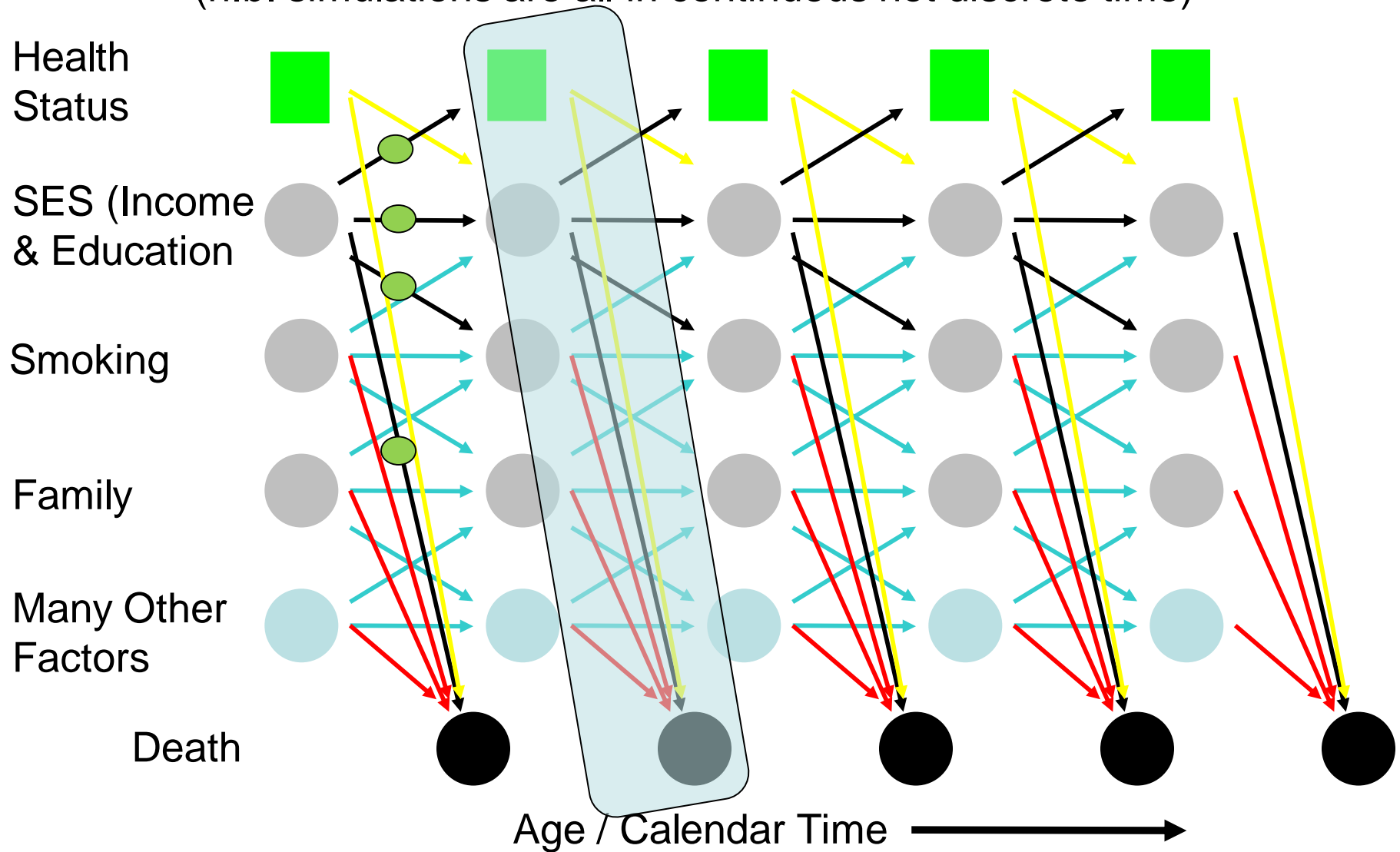
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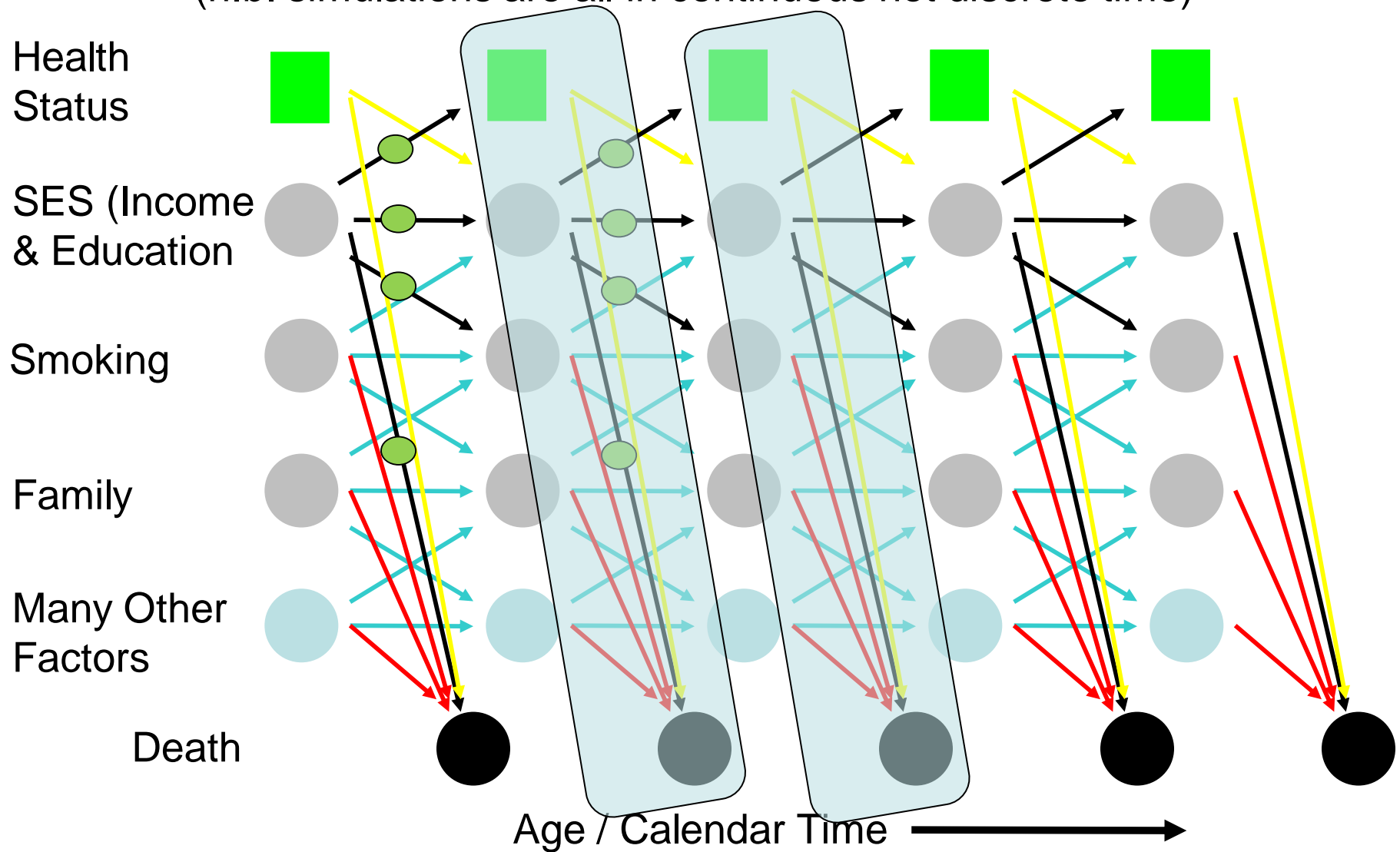
Step 2: Recursive Simulations, Both Baseline and Counterfactual “Knockout” or “Knock To”

(n.b. simulations are all in continuous not discrete time)



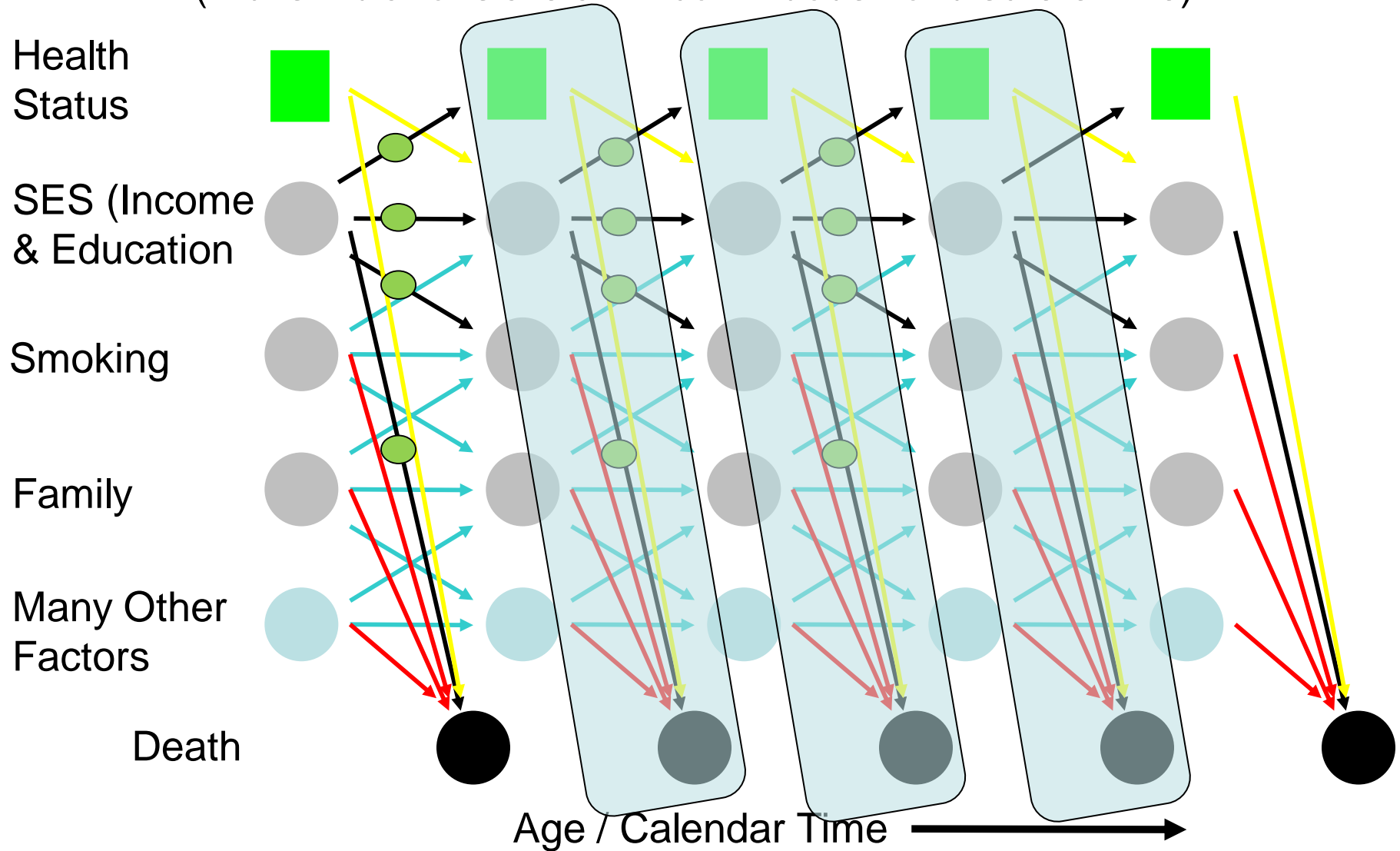
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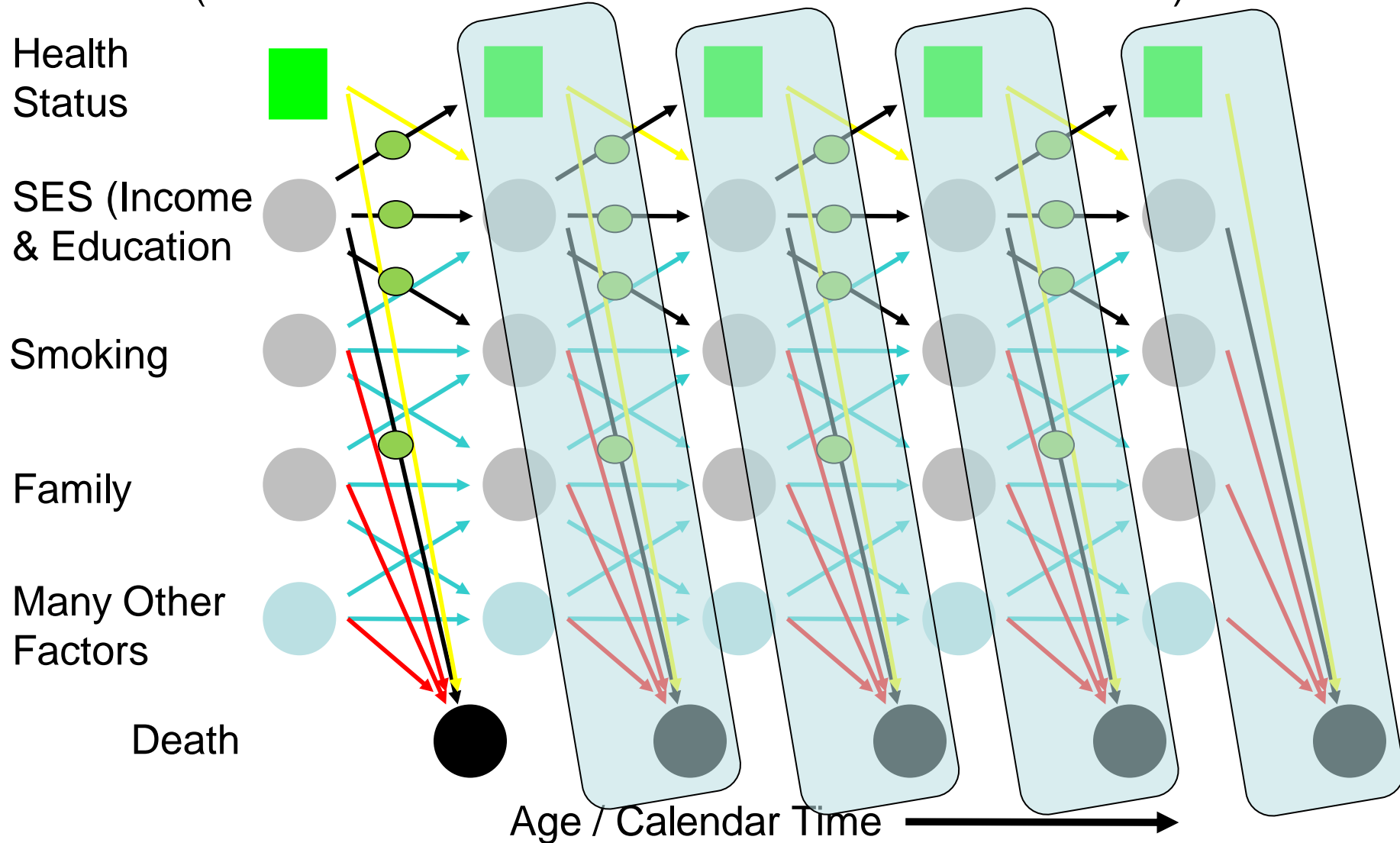
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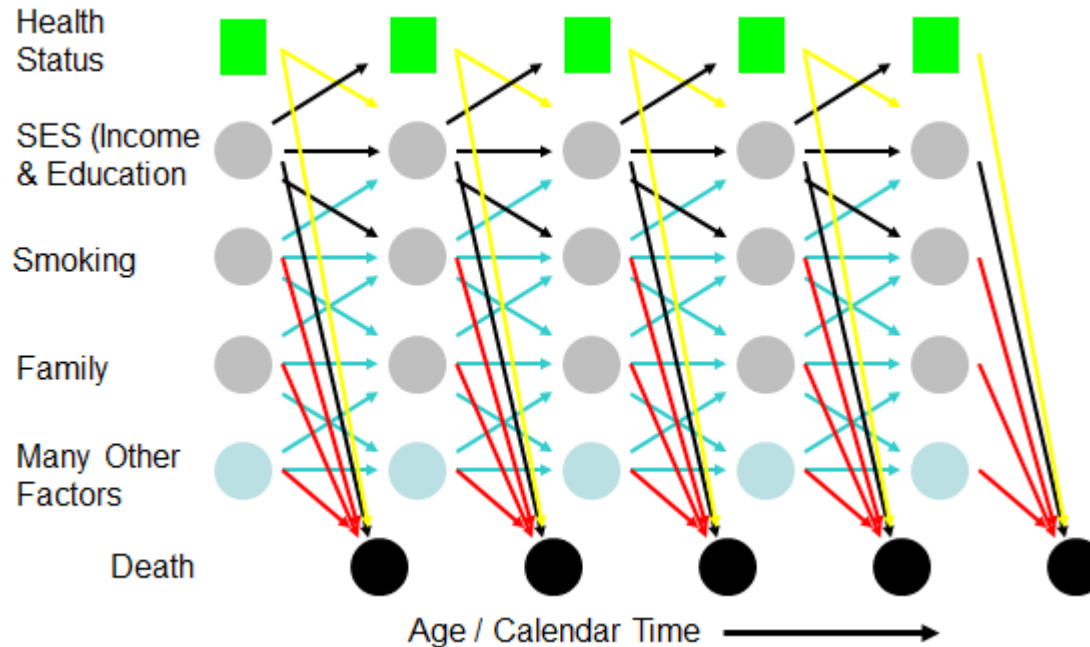


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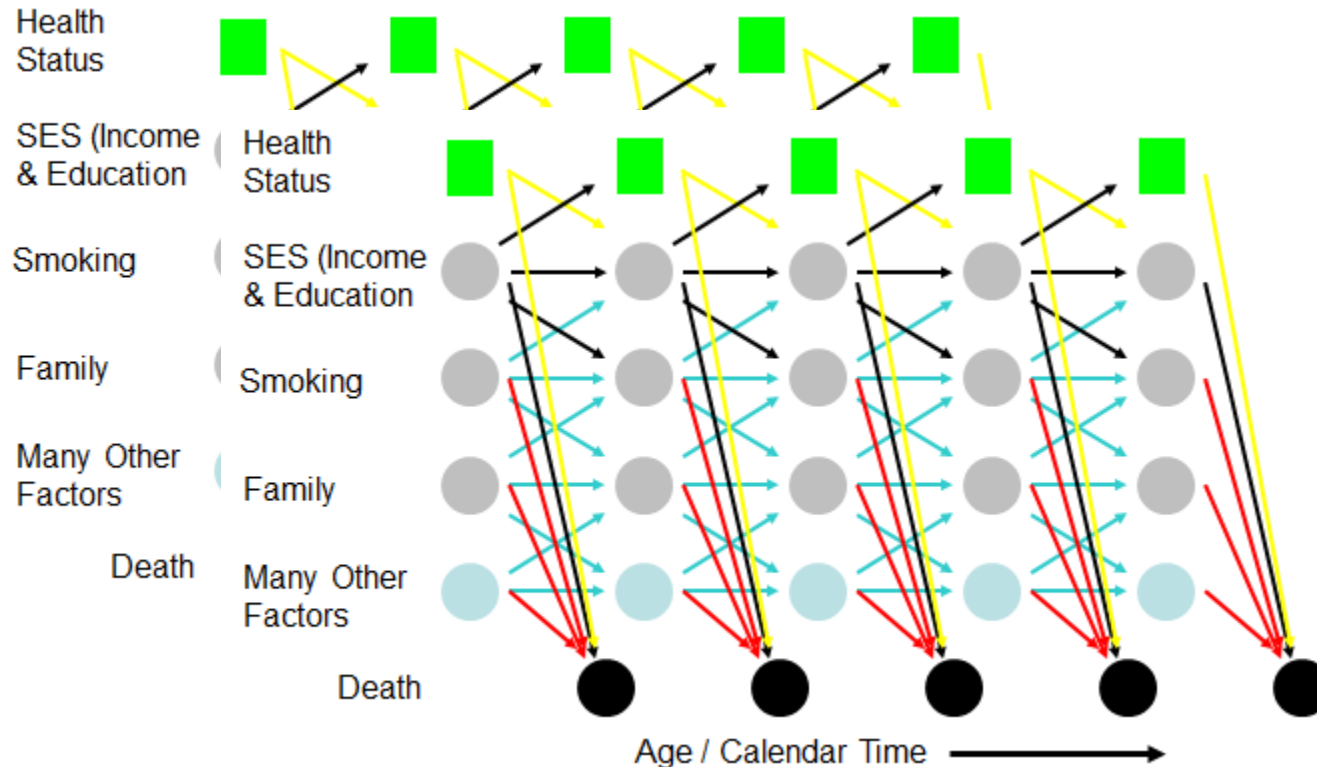
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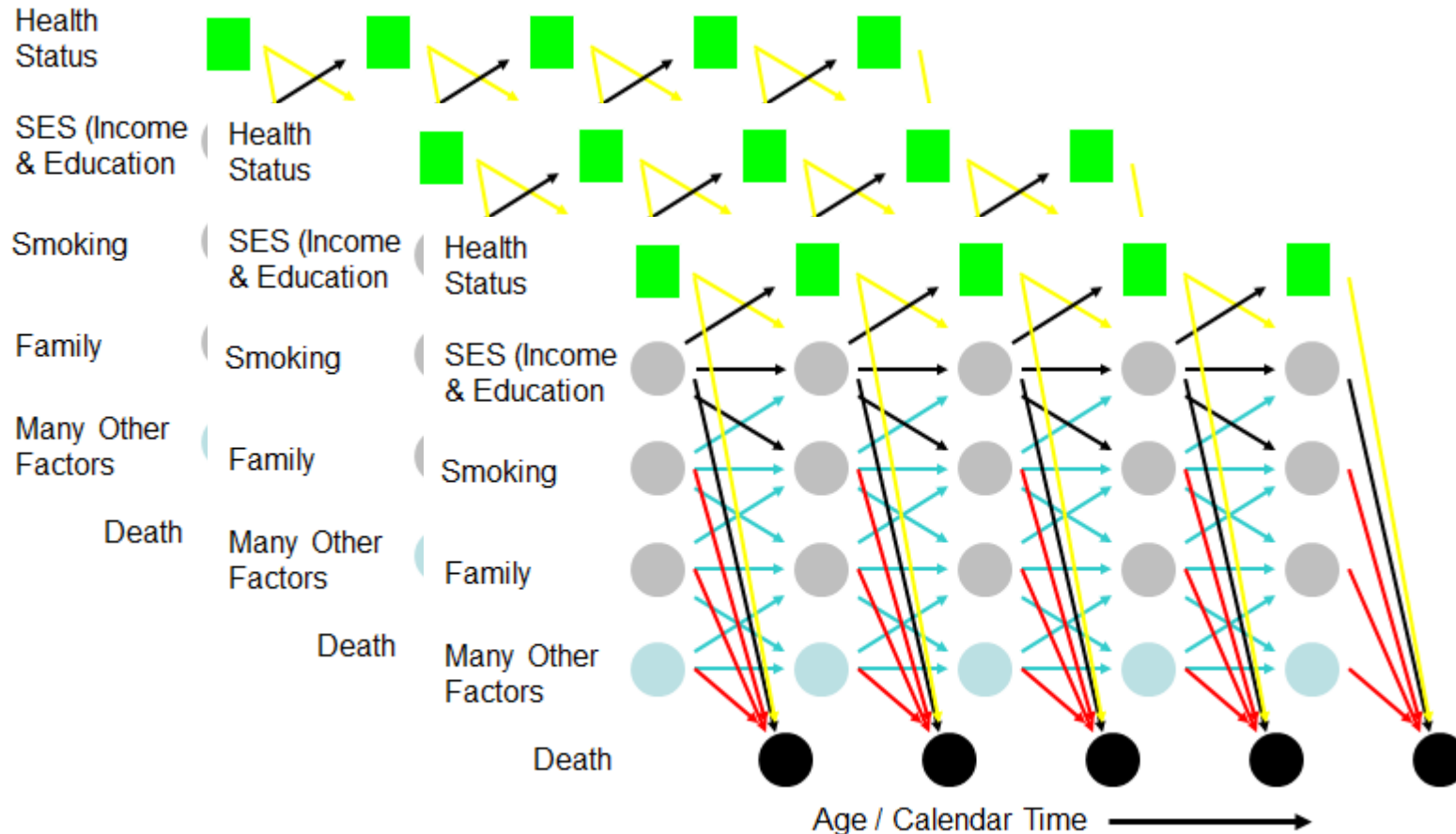
Finally, Repeat Millions of Times; Many Calls to Random Number Generators = Monte Carlo Simulation; Both for Baseline and for Counterfactual Runs



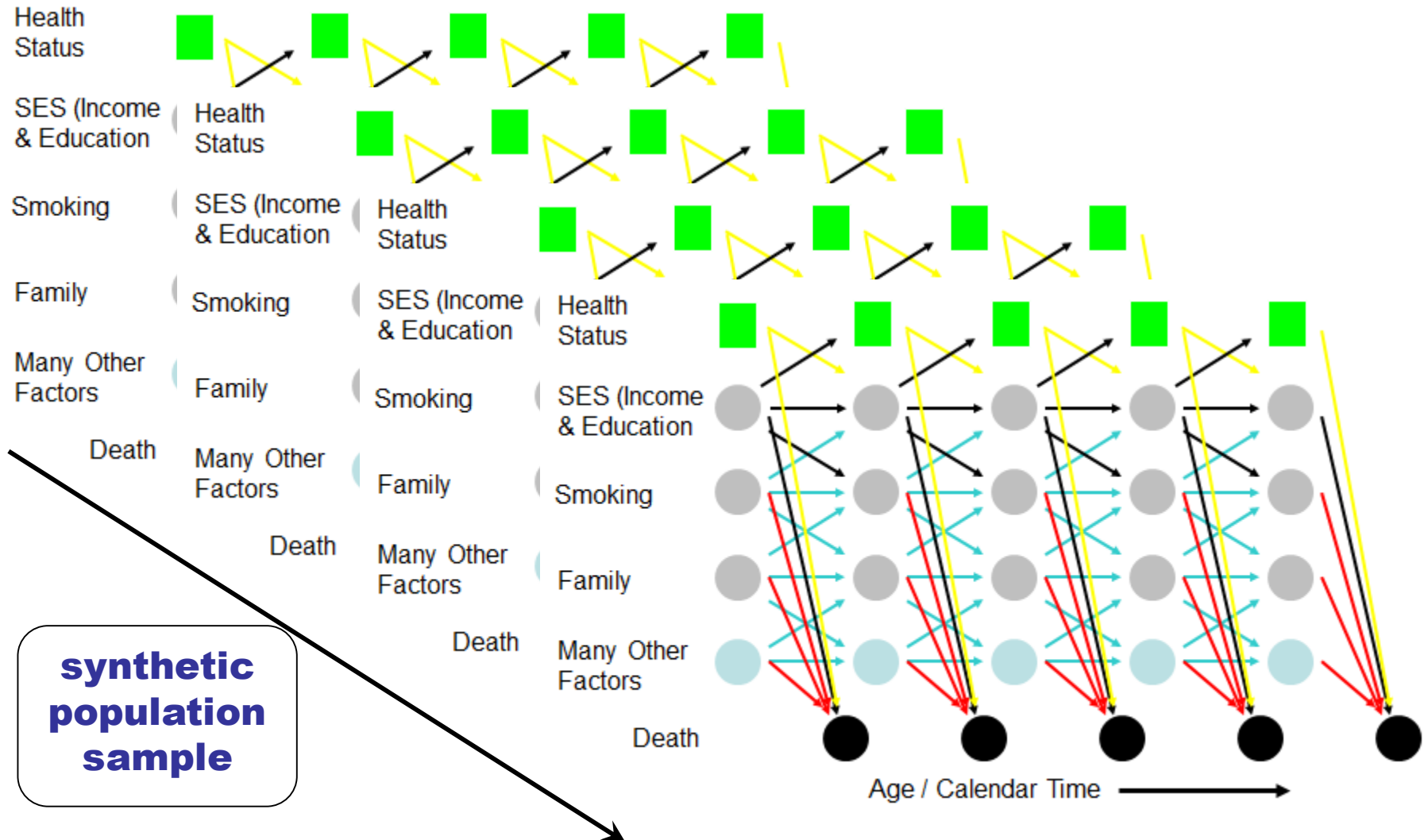
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HealthPaths – “Explainability”

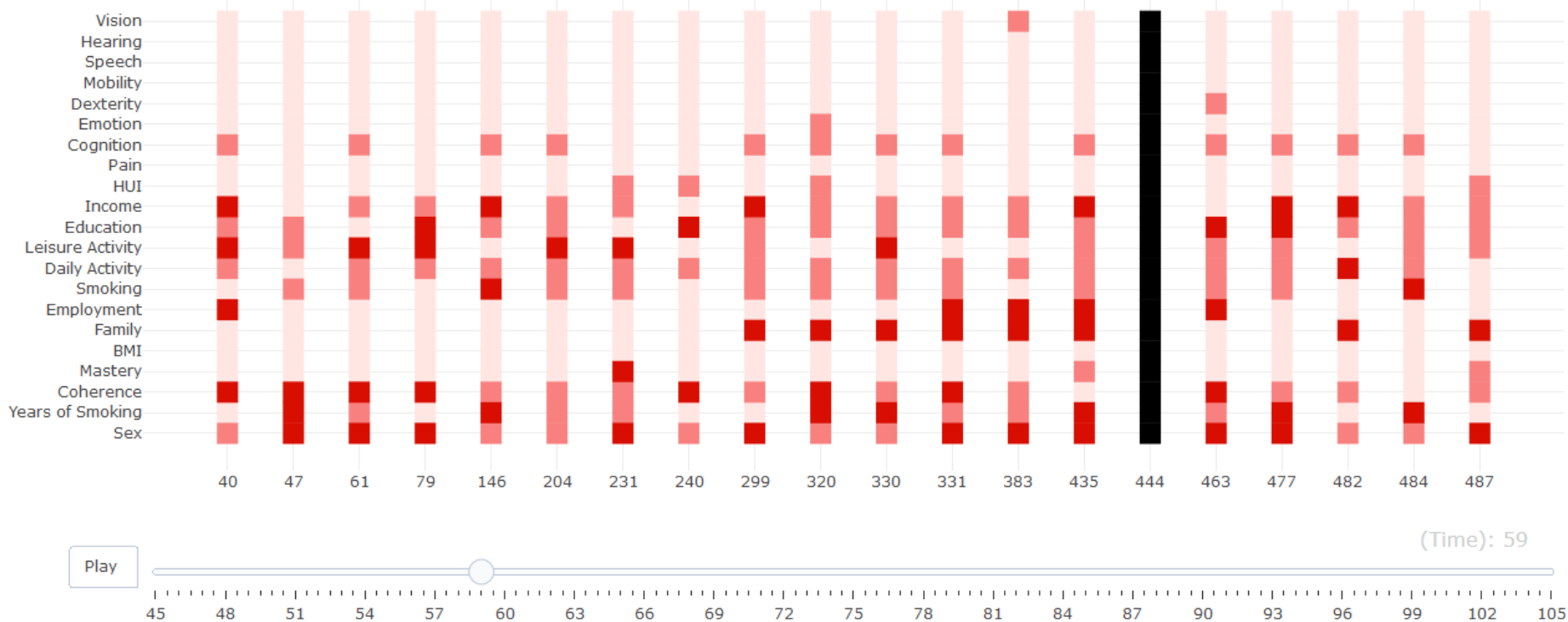
- model has very detailed statistical estimation
 - simultaneous estimation of 20 equations where every dependent variable in one equation can be an independent variable in another (+ interaction terms)
 - NPHS sample bootstrap weights for 40 replicates
 - elastic net regression (weighted average of ridge & lasso) + out-of-sample prediction errors
- thus it is impossible to assess statistical estimation by inspecting input coefficients
- alternative: use data visualization to explore intermediate results of simulations and to support “explainability” of the results

HealthPaths – Three Visualization Animations

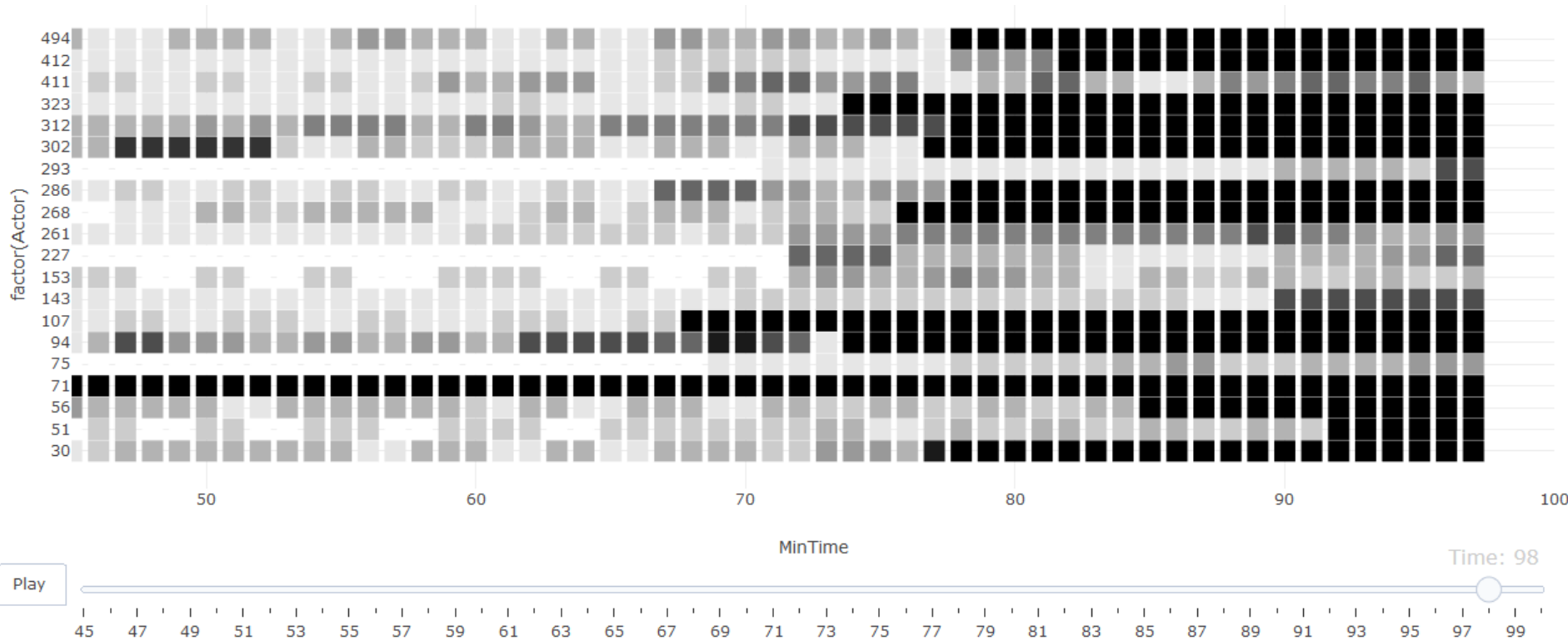
- co-evolving HealthPaths state variables for a small sample of simulated biographies
- evolving HUI (health utility index) values for a small sample
 - underlies the HALLs and calculation of HALE
- evolving strengths of correlation between HUI at age a and covariates at age $a-1$ year

(need to switch software...)

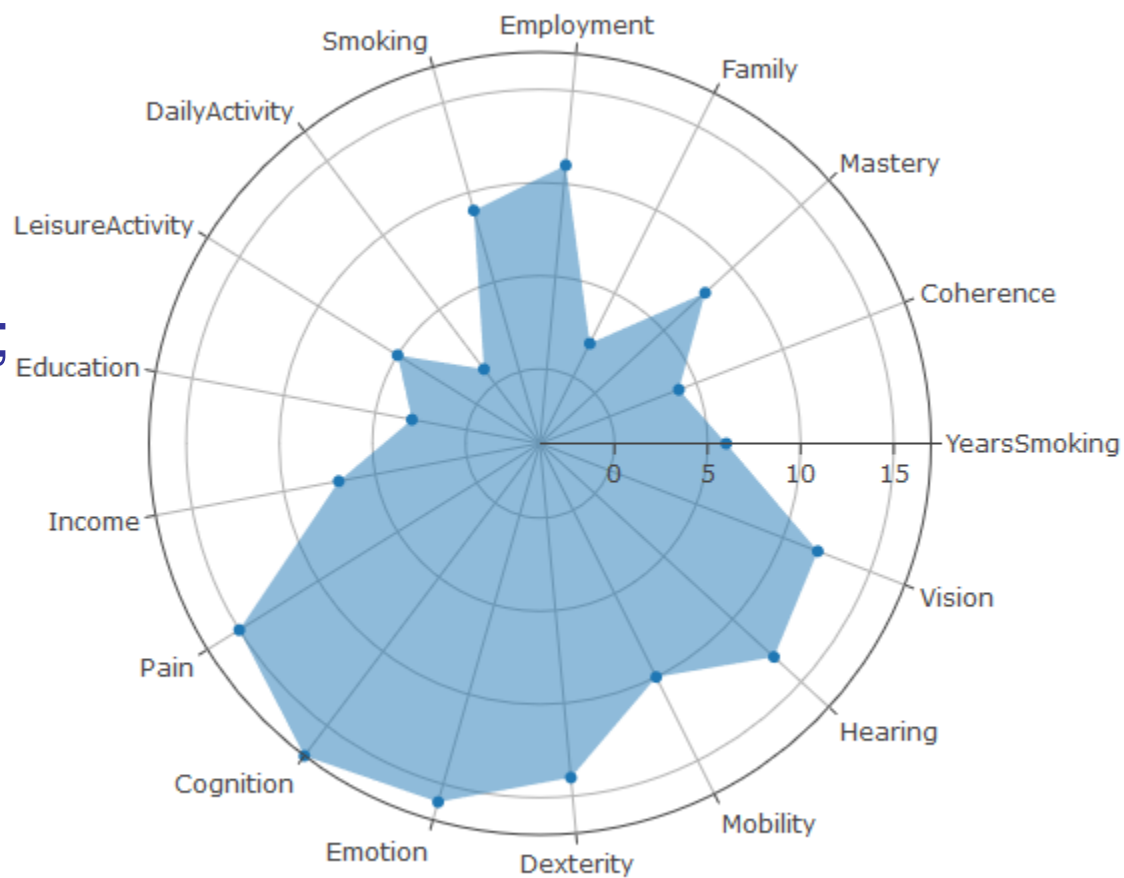
(this is a screenshot from an animation of a random sample of 20 simulated HealthPaths biographies (across horizontal axis), currently showing the co-evolving state-space variables (vertical axis) at about age 59 (slider across bottom) with 4 colours indicating (sometimes compressed) levels, using R package plotly; all dark indicates dead)



(this is another screenshot of a sample of 20 HealthPaths synthesized biographies (vertical axis) with age (and animation control slider) along the horizontal axis, and the gray-shade levels corresponding to a (4-way categorization) of the McMaster Health Utility Index (HUI) values, again using R package plotly)



(this is a screenshot of one of a series of animated (over age) radar plots showing rank order correlations for each of several state space variables, this time for a random sample of 500 HealthPaths biographies; the key idea is to show that a dependent variable from one perspective can be an independent variable from another, i.e. that they all co-evolve, albeit with varying levels of influence, using plotly)



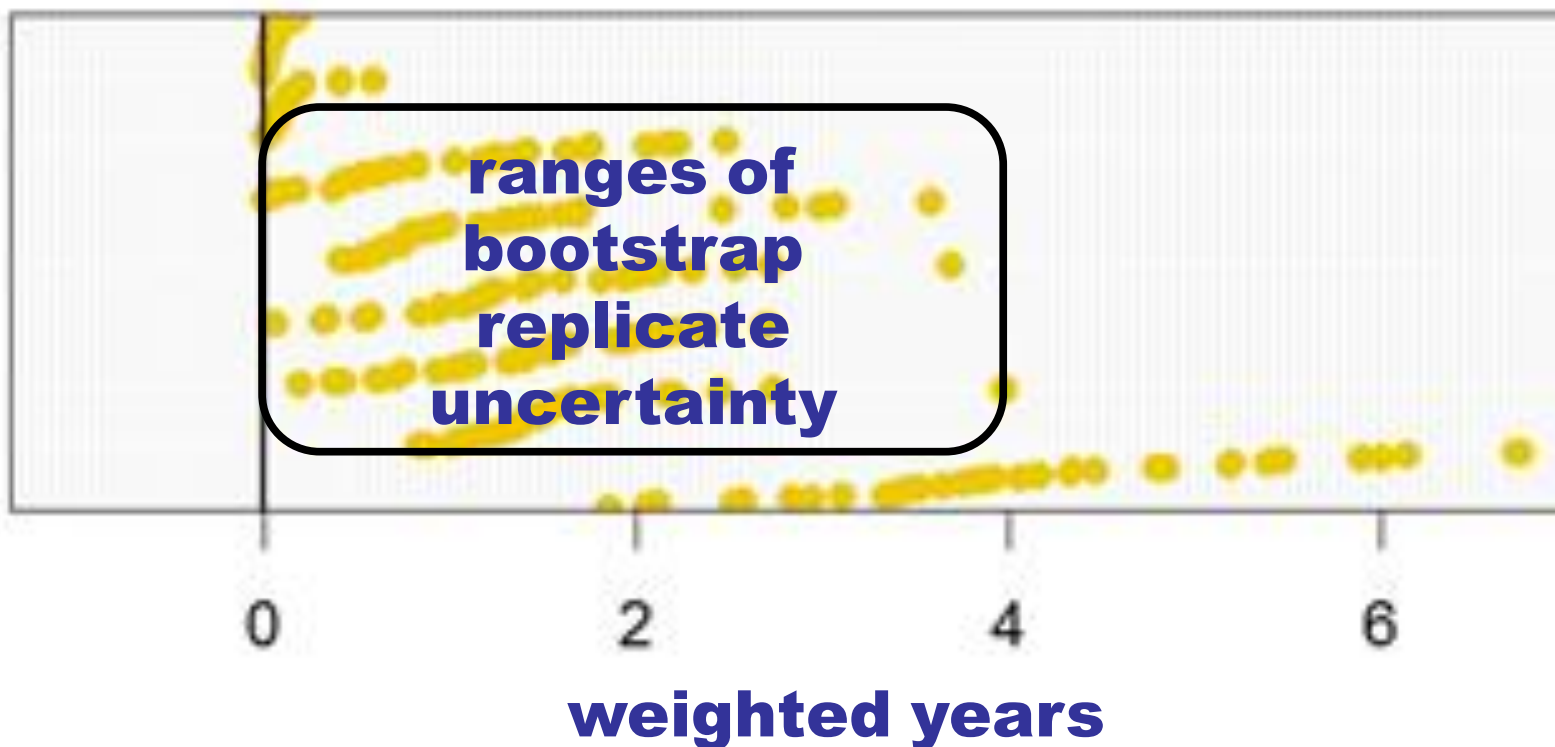
HealthPaths – Results

- first, simple “cause-deleted” impacts of main components of the Health Utility Index (HUI)
- second, “cause-deleted” impacts of widely accepted health determinants
- then counter-factual simulations to explore the impacts on health inequalities of three “unjust” \equiv ameliorable sources

Functional Health Impacts on HALE by HUI domain for Men (years)

(Each Dot = 1 Bootstrap Replicate $\Rightarrow 8 \times 40 = 320$
Counterfactual plus 320 Baseline Simulations)

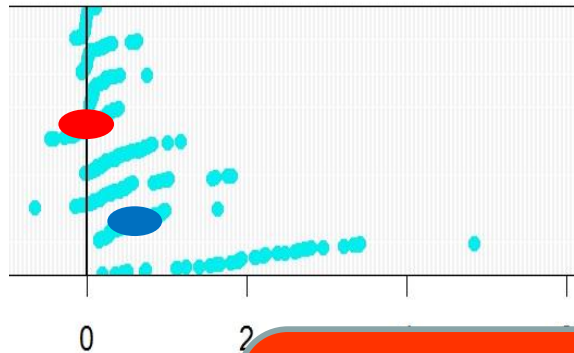
Dexterity
Speech
Mobility
Emotion
Hearing
Pain
Vision
Cognition



Functional (HUI) Health Impacts, LE and HALE, Men and Women

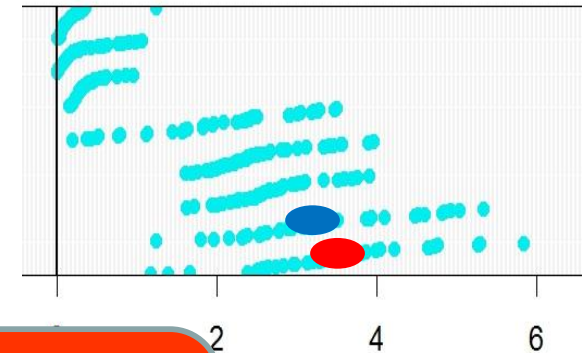
LE: Women

Speech
Dexterity
Hearing
Pain
Emotion
Vision
Cognition
Mobility



HALE: Women

Speech
Dexterity
Hearing
Mobility
Vision
Emotion
Cognition
Pain

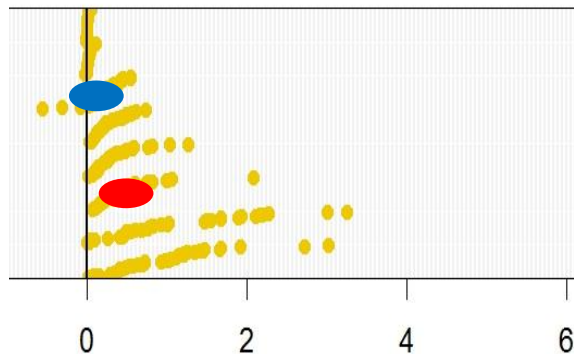


pain (esp. women) and cognition
(esp. men) most discrepant
between LE & HALE

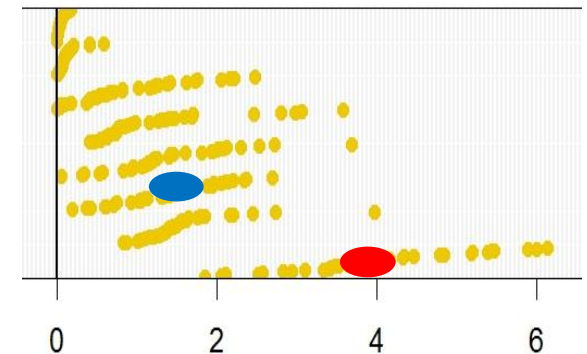
Weighted Years

HALE: Men

Dexterity
Speech
Pain
Emotion
Vision
Cognition
Mobility
Hearing



Dexterity
Speech
Mobility
Emotion
Hearing
Pain
Vision
Cognition



Weighted Years

Composite Risk Factors Defined

- BMI, smoking, family membership, employment – used directly
- Socio-Economic Status (SES) = Education + Income
- Physical Function = Leisure + Daily Non-leisure + Mobility + Dexterity
- Mental Condition = Sense of Coherence + Sense of Mastery + Emotion + Cognition
- Sensory Function = Vision + Hearing + Speech + Pain

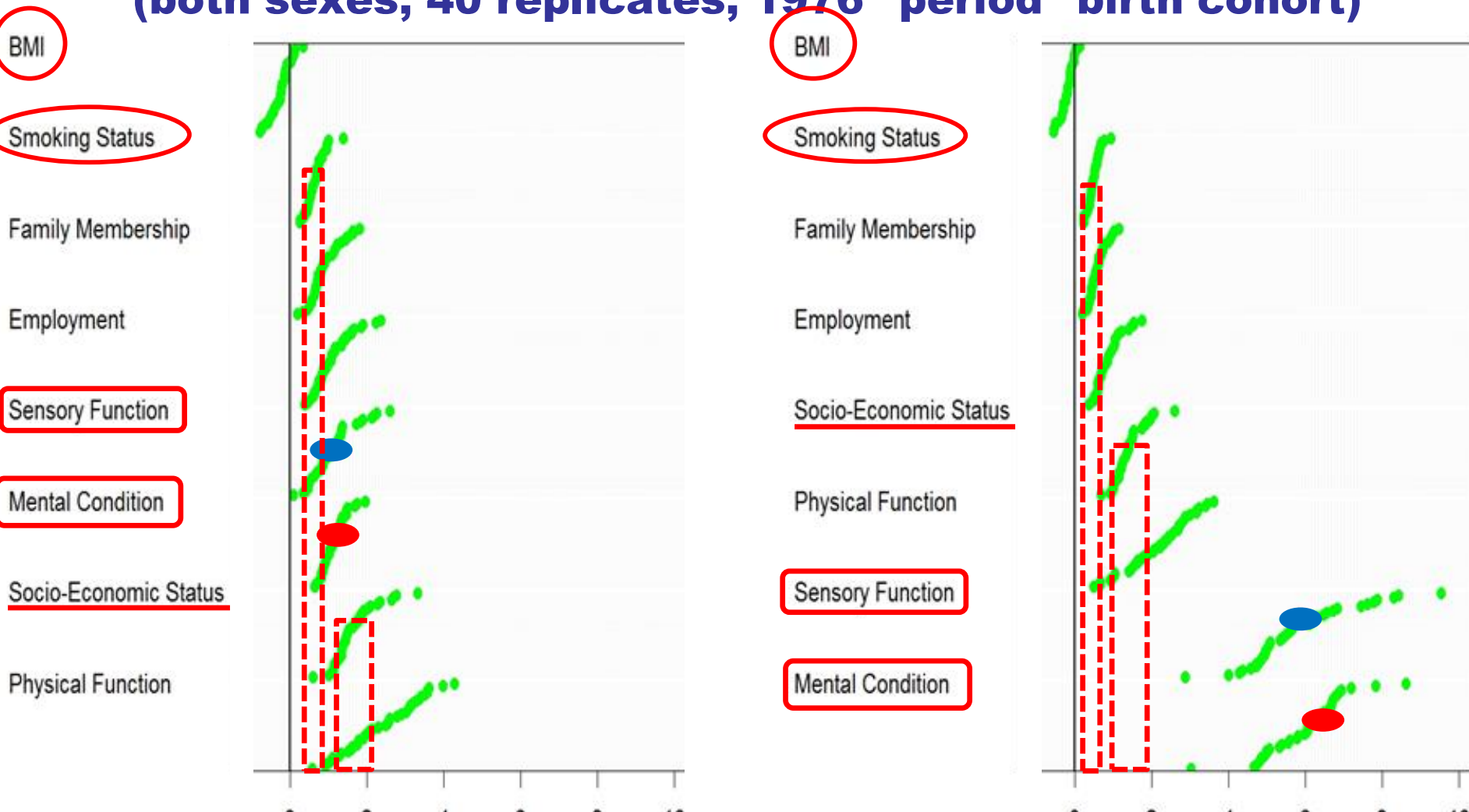
Composite scenarios fix a set of variables at 'optimal' scores (eg. for SES, everyone is a university graduate with income always in the top decile)

Caveats

- associations (even lagged) \neq causality
- errors in variables (e.g. BMI)
- “composite risk factors” mixing apples and oranges?
- many omitted variables (but fewer than many other studies)
- construct validity: are the variables intrinsically as intended (“*indicatum*”), or merely “markers”?
- 1976 period birth cohort (e.g. male smoking rates considerably lower)
- choice of comparator in counterfactual (e.g. top income decile, great sense of coherence)

Impacts “As If” Each Composite Risk Factor Were “Optimal” – Years Gained

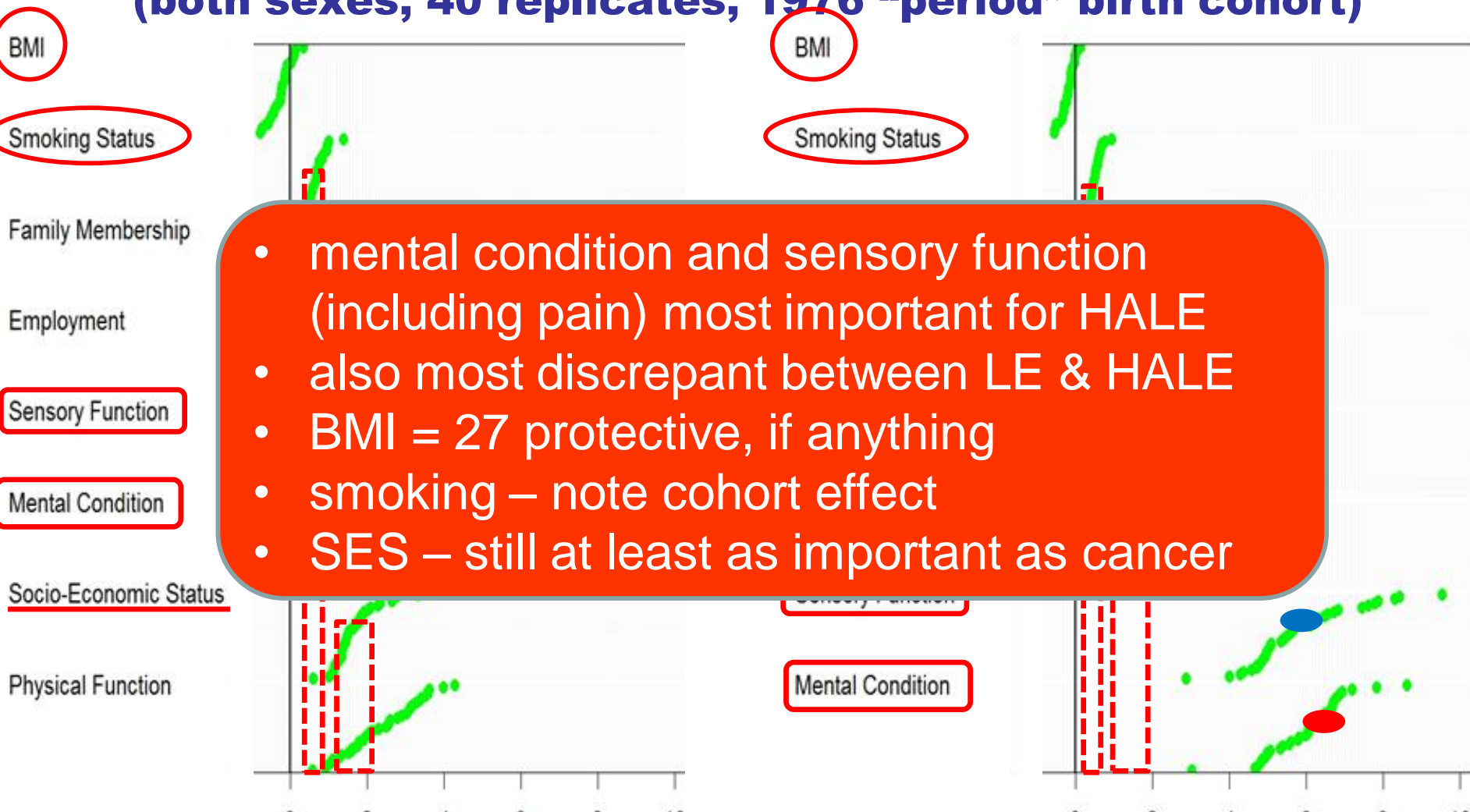
(both sexes, 40 replicates, 1976 “period” birth cohort)



(n.b. thinking through the interpretations of these counter-factuals is still novel for epidemiology, and will benefit from further discussion)

Impacts “As If” Each Composite Risk Factor Were “Optimal” – Years Gained

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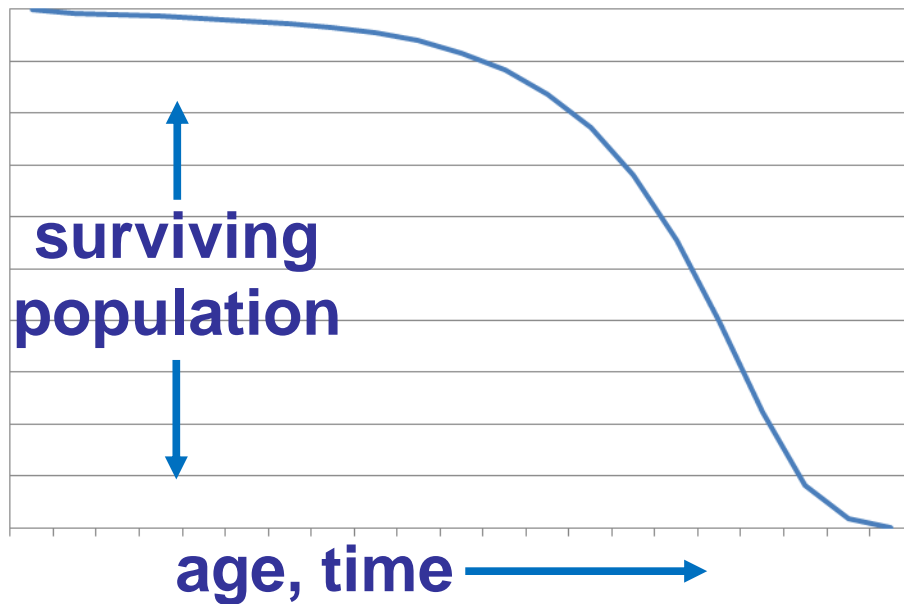
(n.b. thinking through the interpretations of these counter-factuals is still novel for epidemiology, and will benefit from further discussion)

Let us now look at counterfactuals designed to assess sources of health inequalities

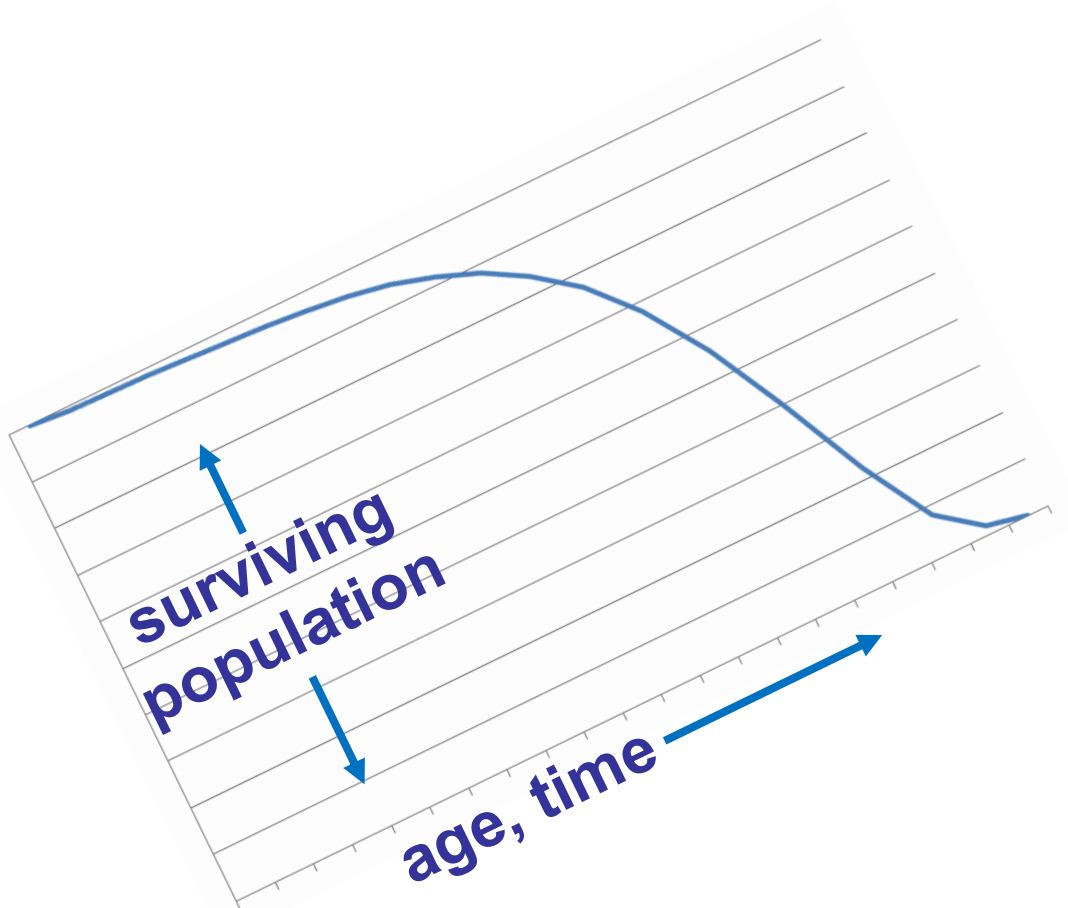
**Recall that we need to use a
univariate health inequality
approach**

- LL = life length
- HALL = health-adjusted life length
- for large samples of simulated individual life course trajectories

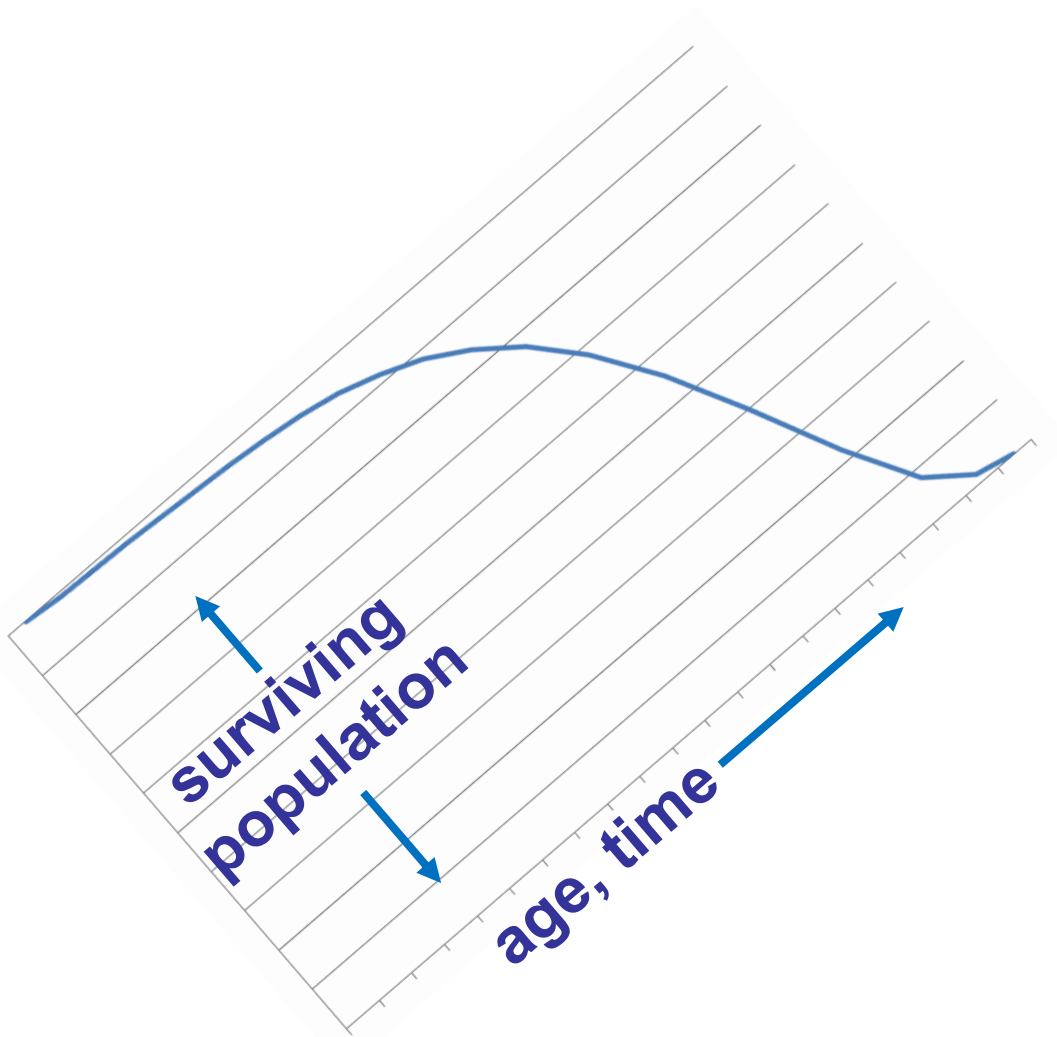
Conventional Survival Curve and Univariate Health Inequality



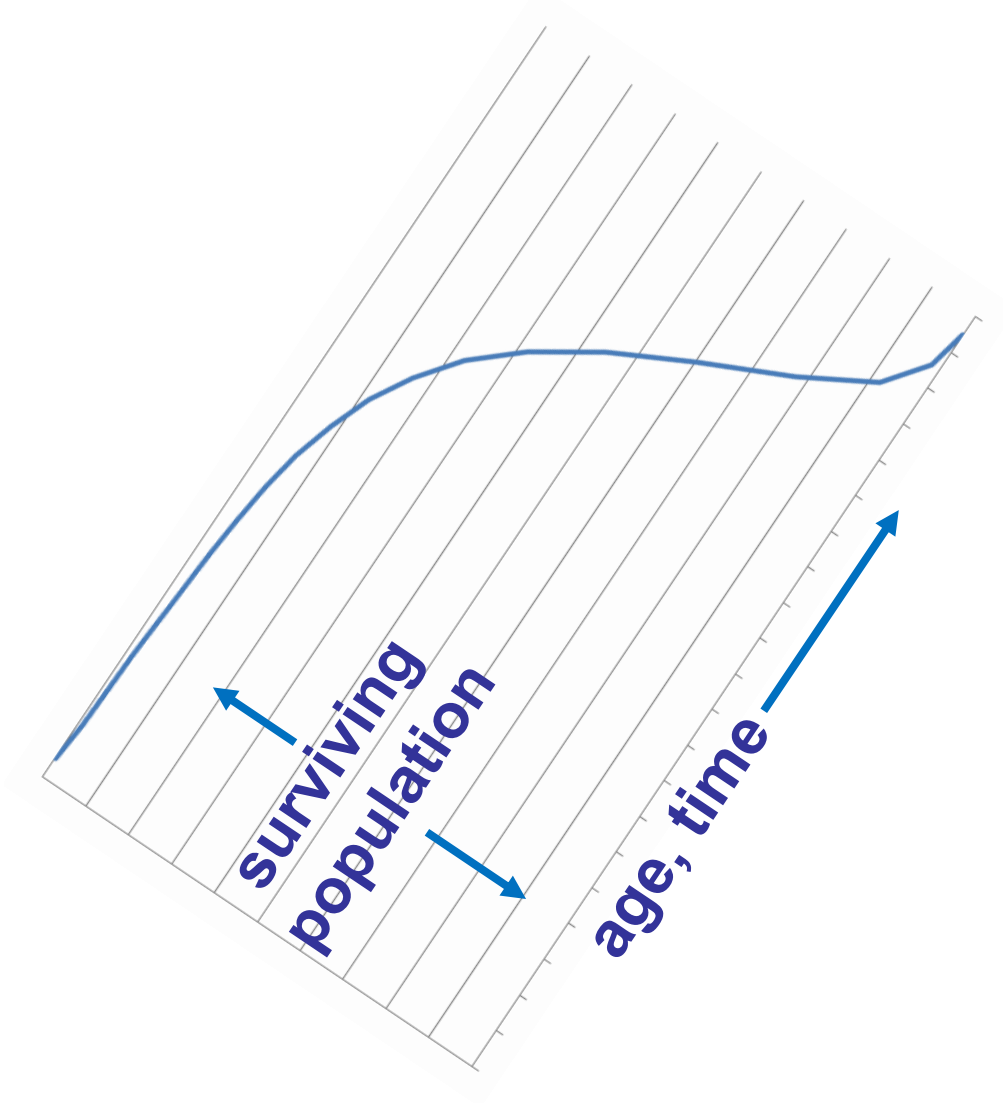
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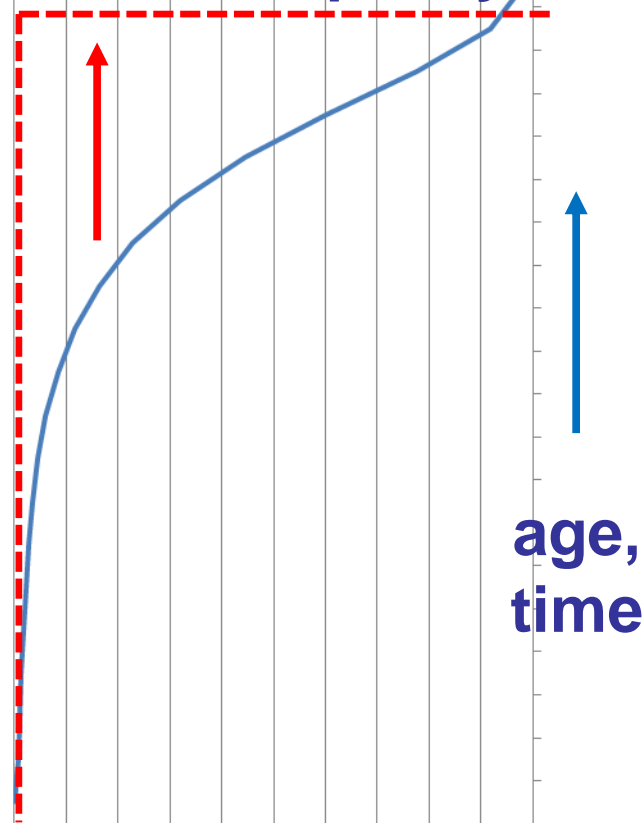


Conventional Survival Curve and Univariate Health Inequality



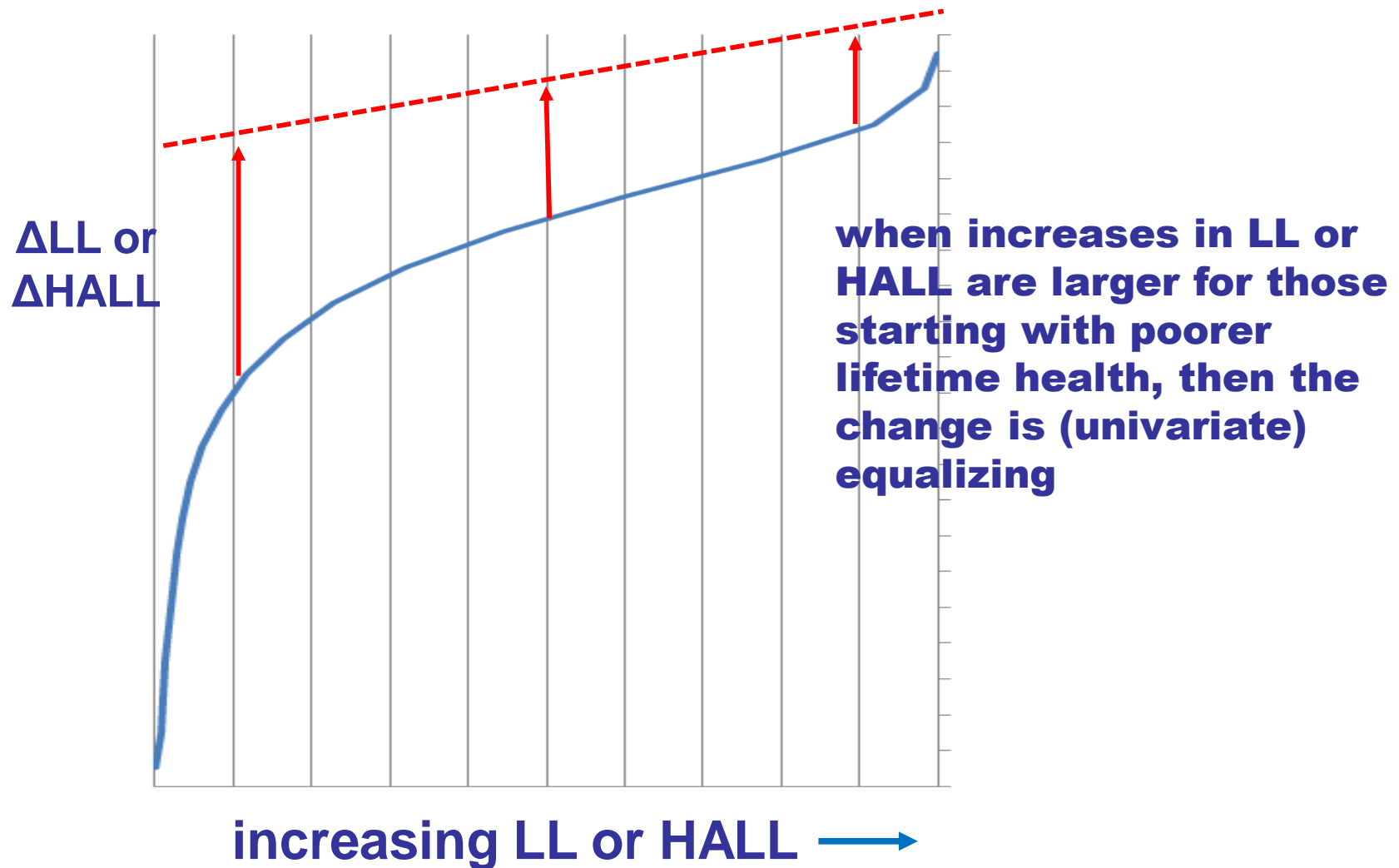
Conventional Survival Curve and Univariate Health Inequality

line of zero univariate
health inequality

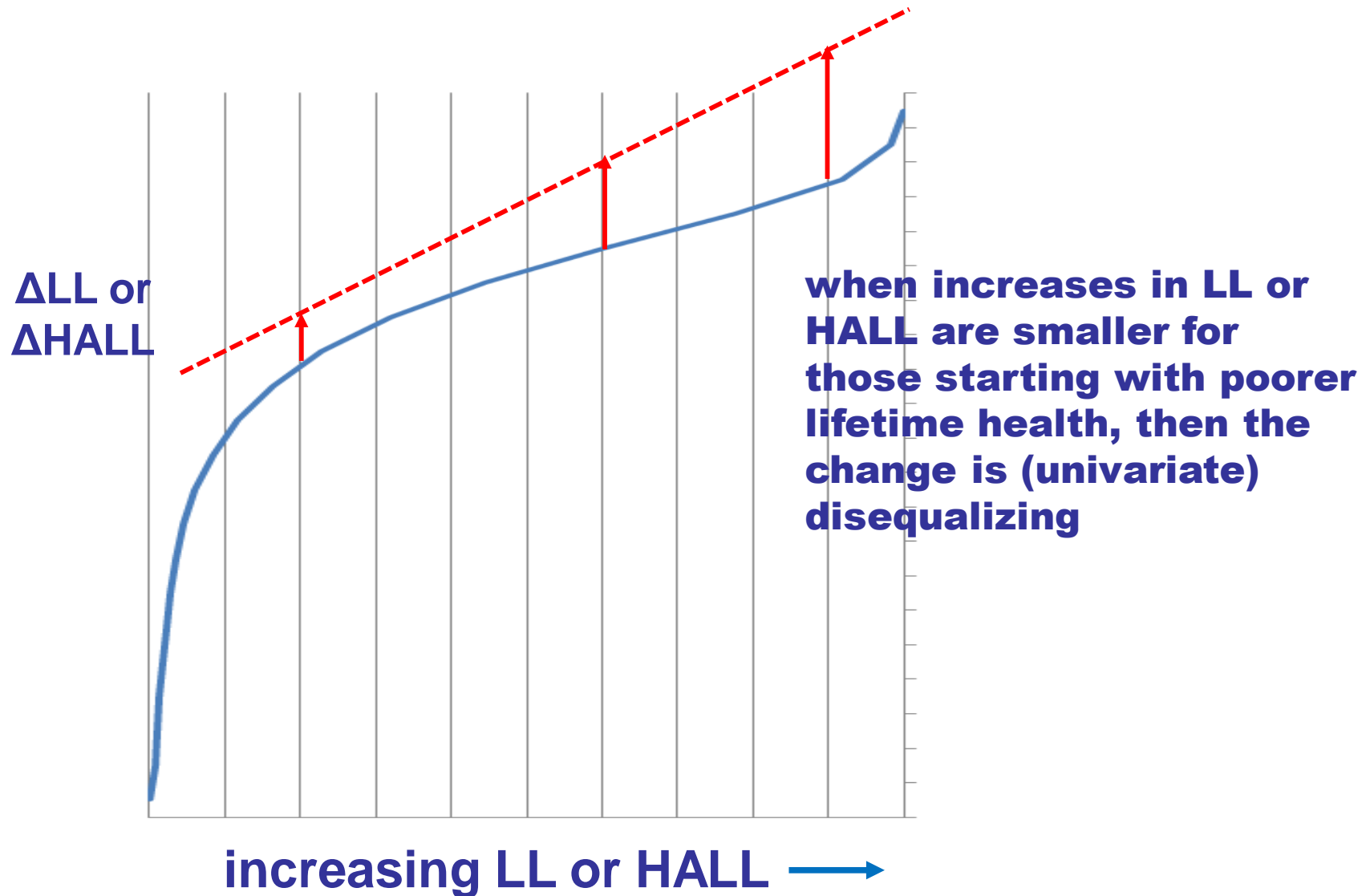


increasing
LL or HALL →

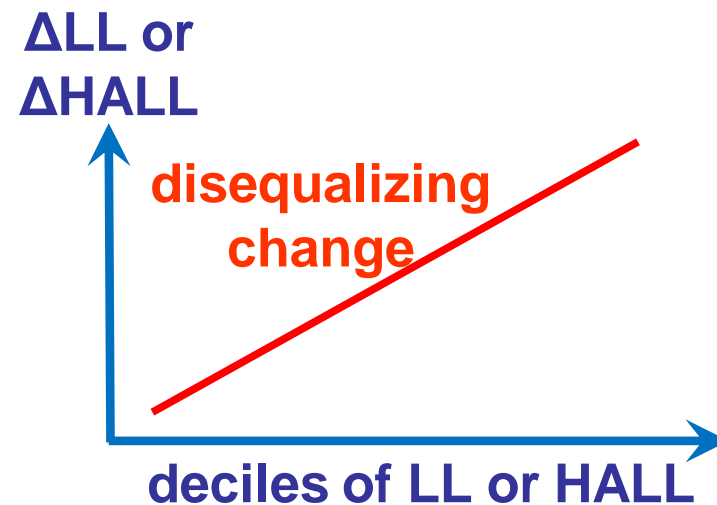
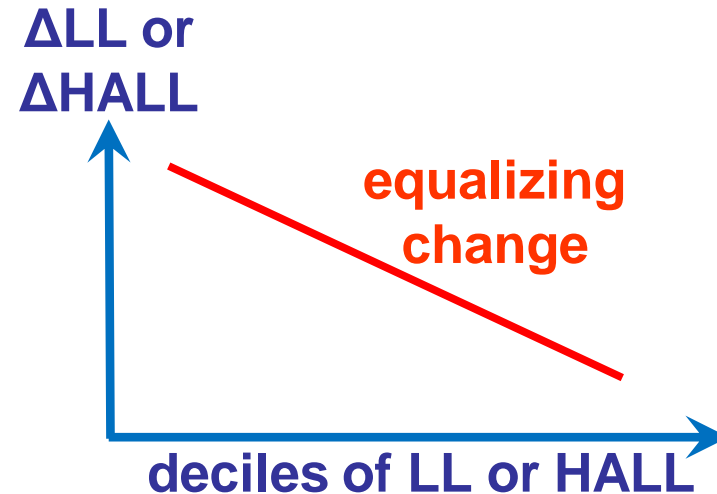
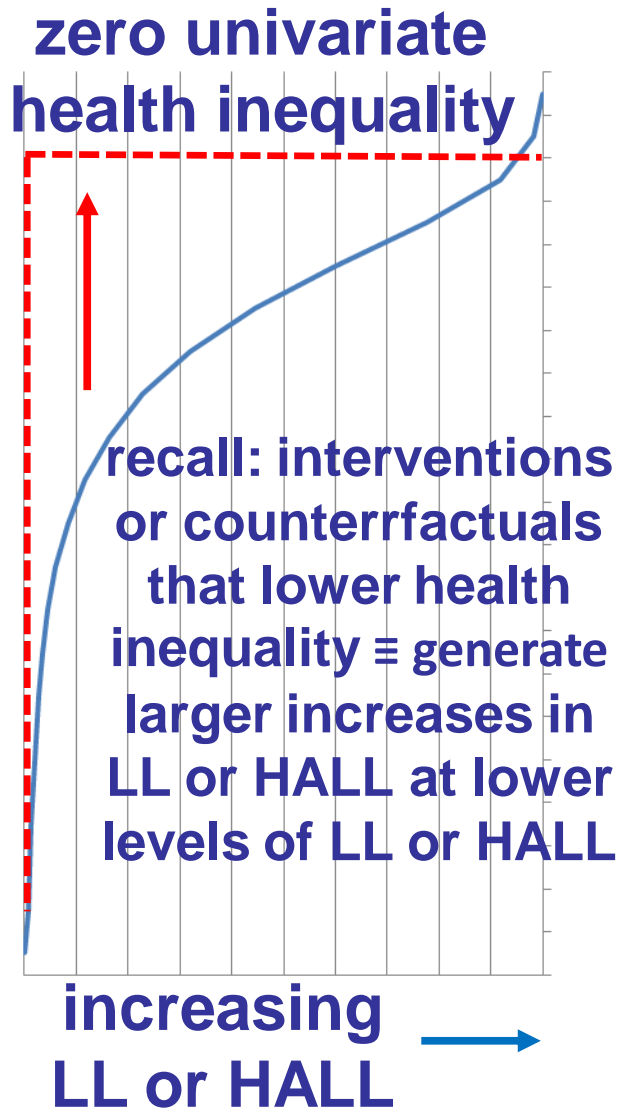
Assessing Univariate Health Inequality from Simulated Counterfactual Changes



Assessing Univariate Health Inequality from Simulated Counterfactual Changes

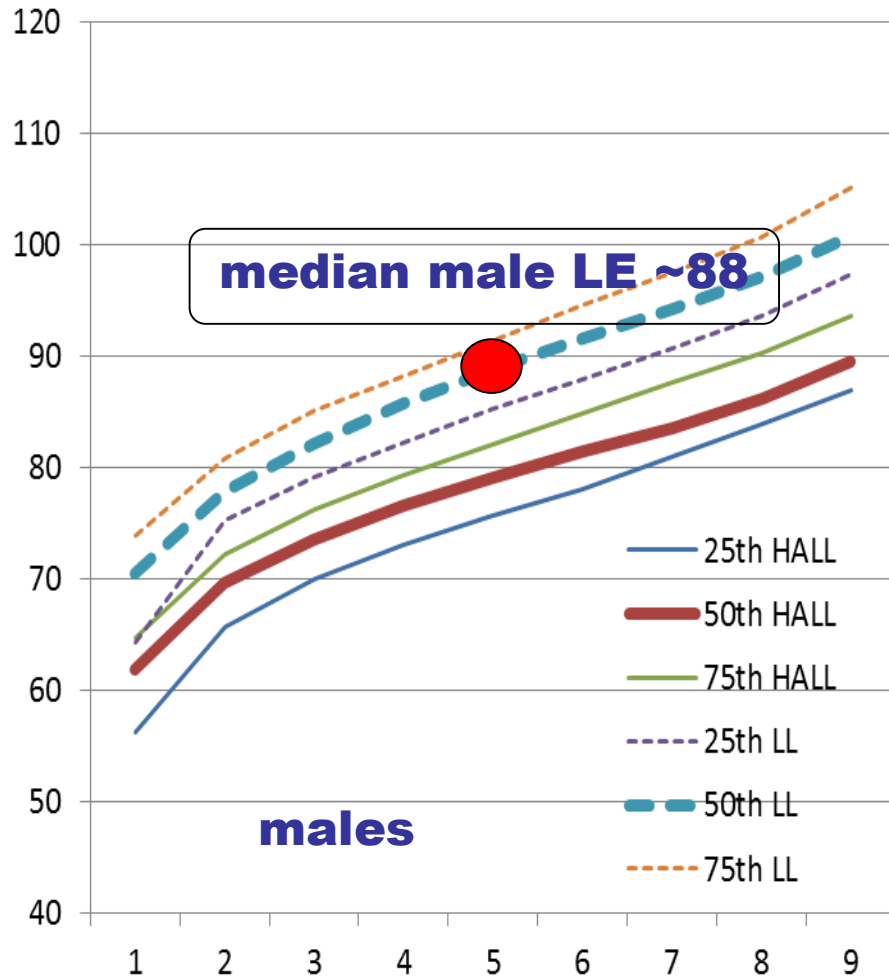


Changes in (Rotated) Survival Curves and Univariate Health Inequality



Baseline LLs (dashed) and HALLs (solid) by Health Decile (horizontal axis), Quartile Distributions for 40 Replicates

years

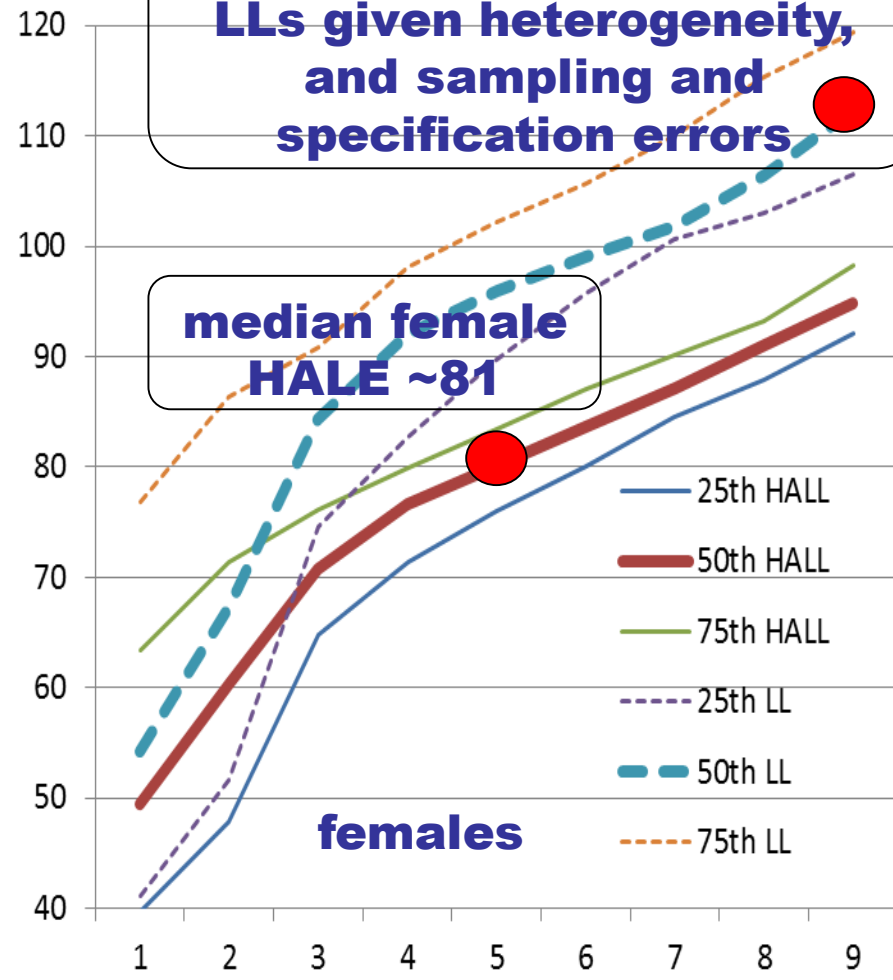


median male LE ~88

males

decile cut-points
of the LL or HALL
distributions

years



90th percentile LL for all
LLs given heterogeneity,
and sampling and
specification errors

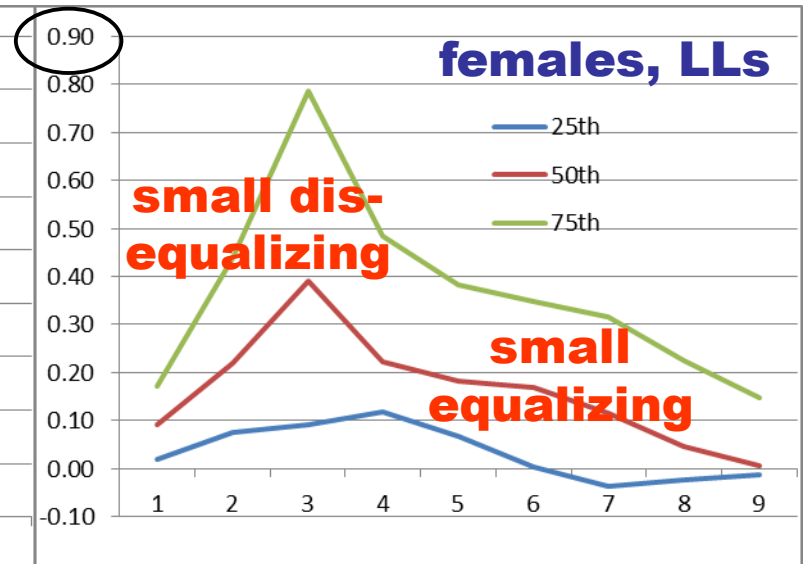
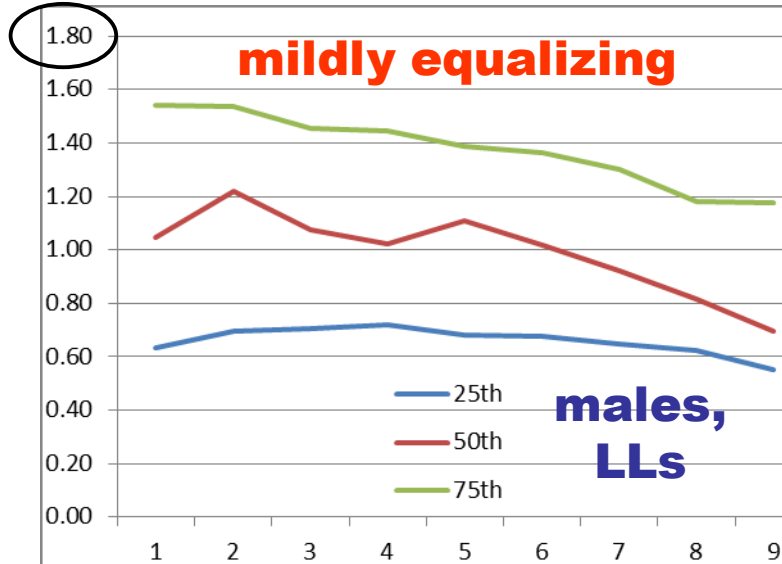
median female
HALE ~81

females

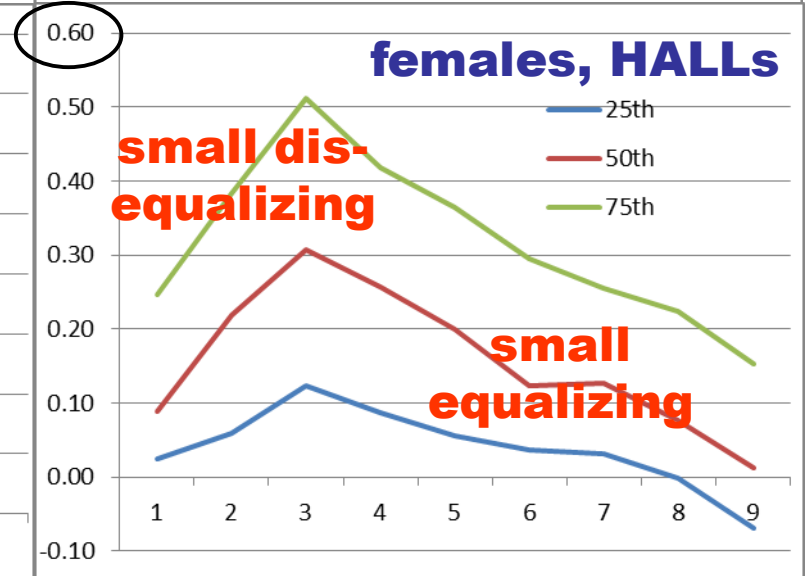
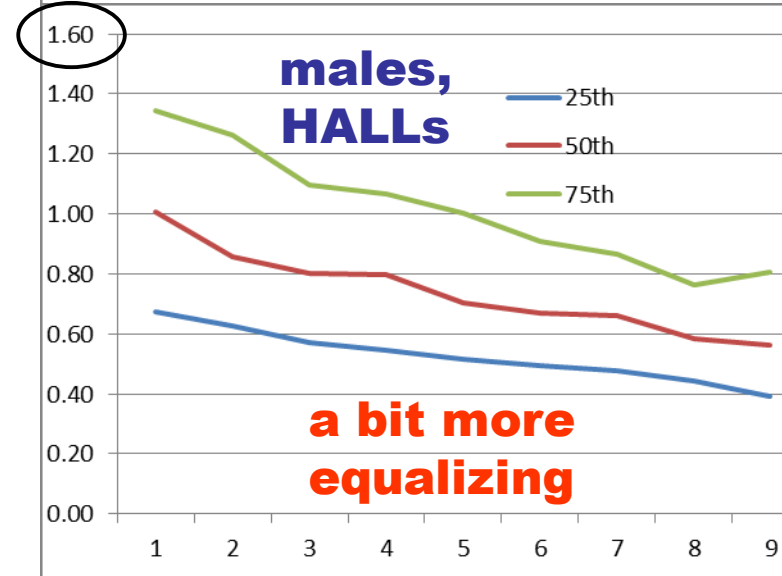
decile cut-points
of the LL or HALL
distributions

No Smoking Scenario Compared to Baseline

Δ LLs
years



Δ HALLs
years



horizontal axes: decile cut-points of the LL or HALL distributions

No Smoking Scenario Compared to Baseline

- eliminating smoking increases **LE** and **HALE** by medians of ~1 year for men, ~0.2 years for women

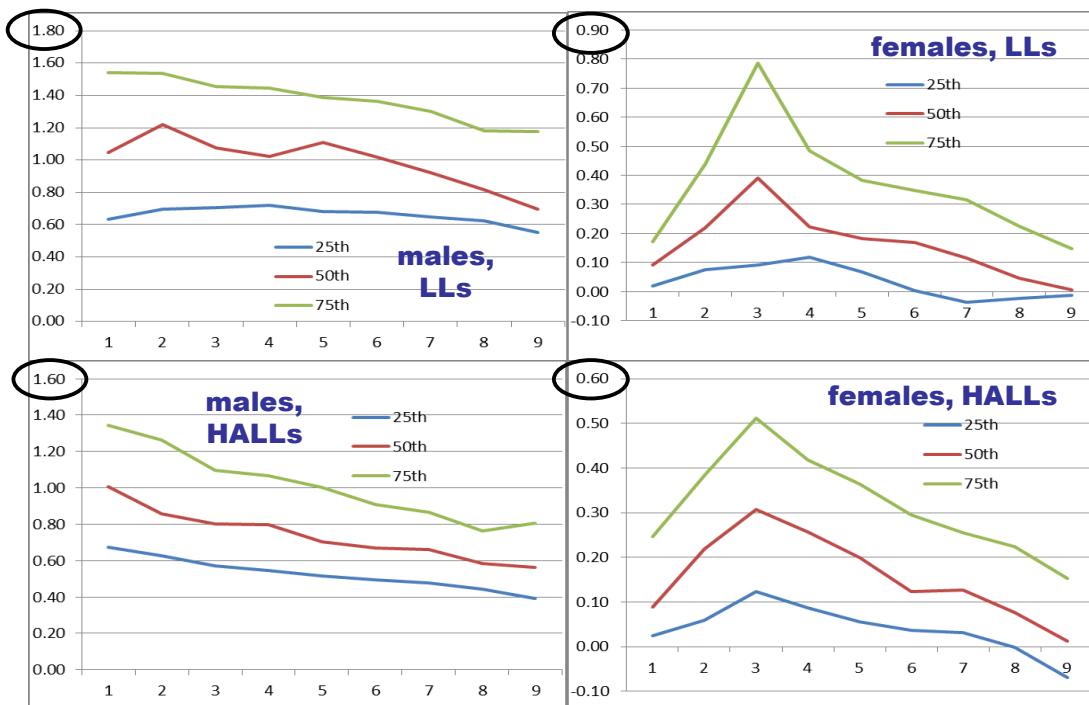
- for men, smoking prevalence decreases with **LL** and **HALL** (i.e. from left to right across the horizontal axis)

- so eliminating smoking for men is associated with greater increases in lifetime health the poorer one's health, hence it is (univariate) equalizing

- for women, smoking is uncommon in general, hence the rather small impact on median **LE** and **HALE**

- it is most common in lower-mid levels of lifetime health

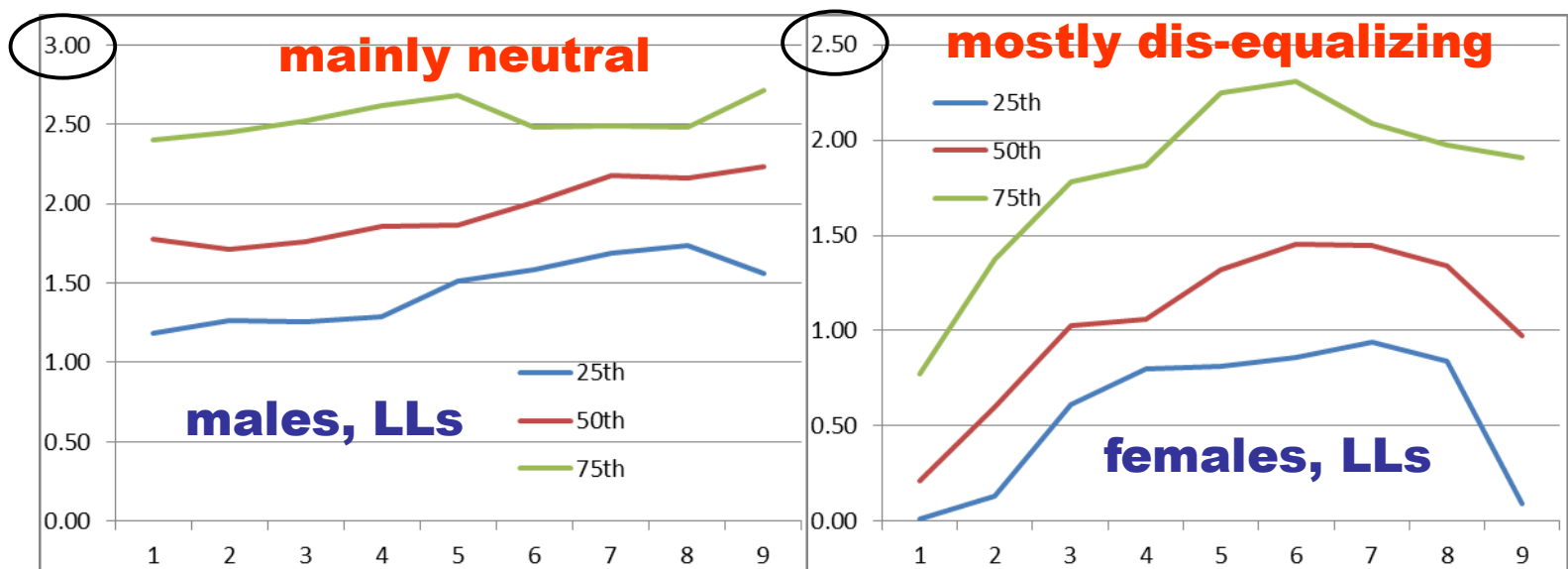
- so for women, eliminating smoking would be associated with the greatest lifetime health improvements in the lower- middle of the health distribution



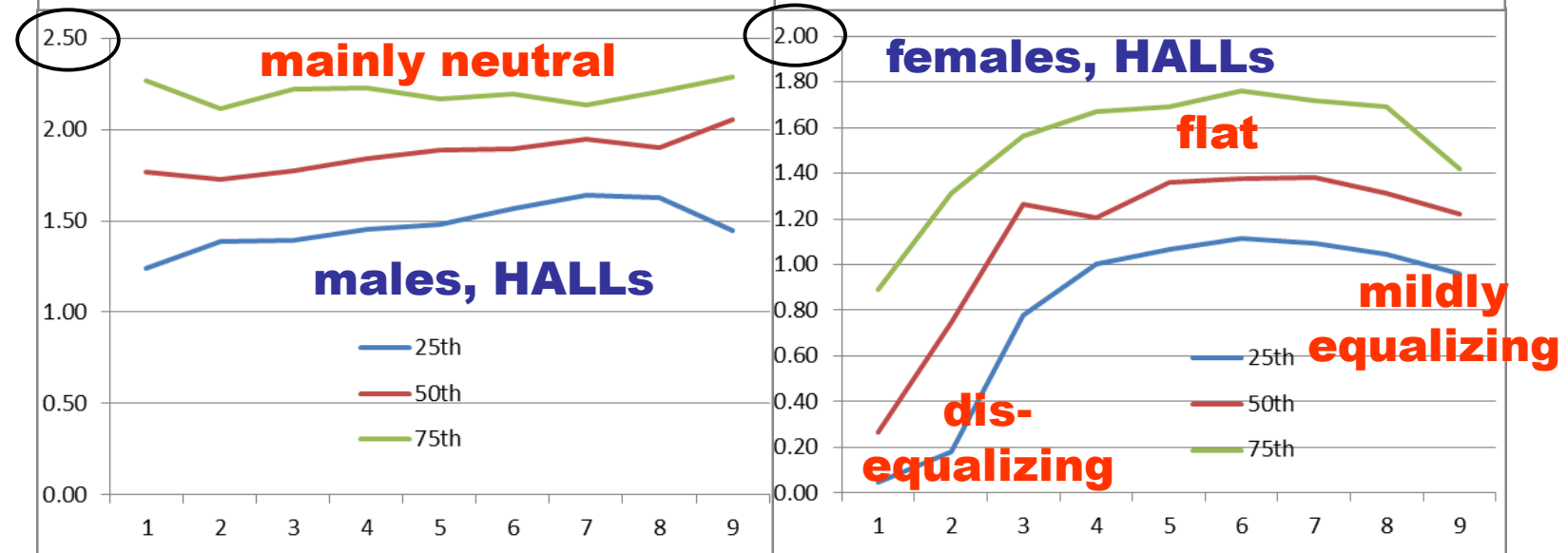
horizontal axes: decile cut-points of the LL or HALL distributions

Top SES Scenario Compared to Baseline

Δ LLs
years

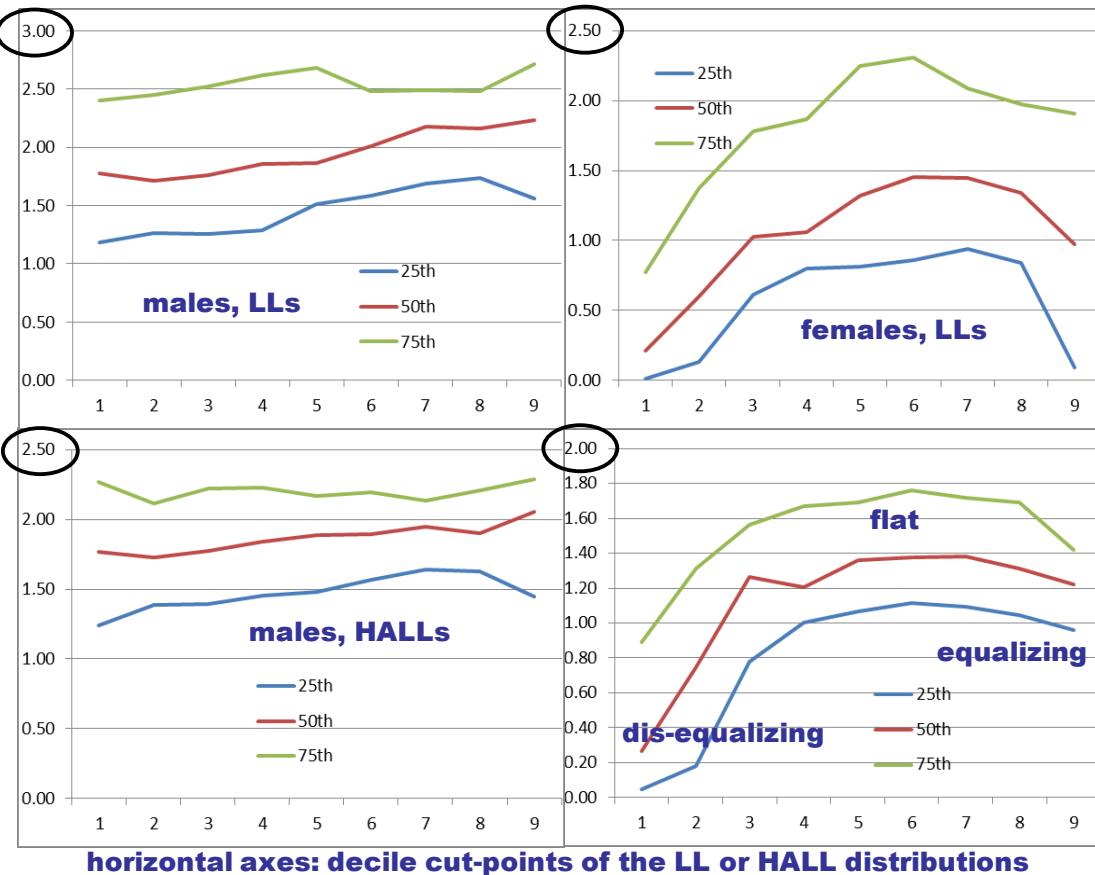


Δ HALLs
years



horizontal axes: decile cut-points of the LL or HALL distributions

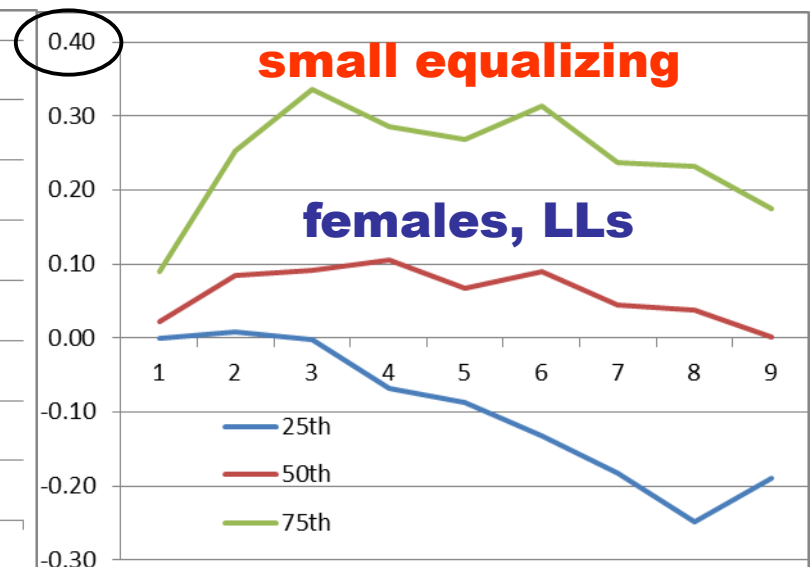
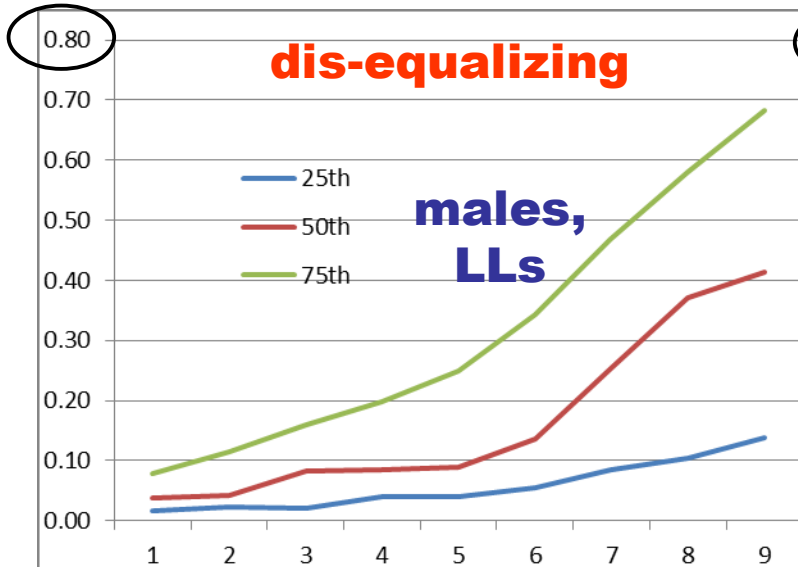
Top SES Scenario Compared to Baseline



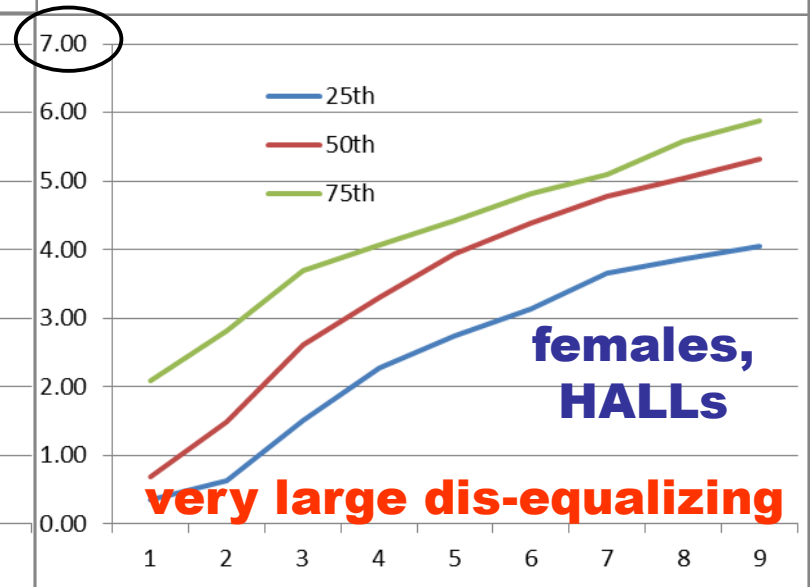
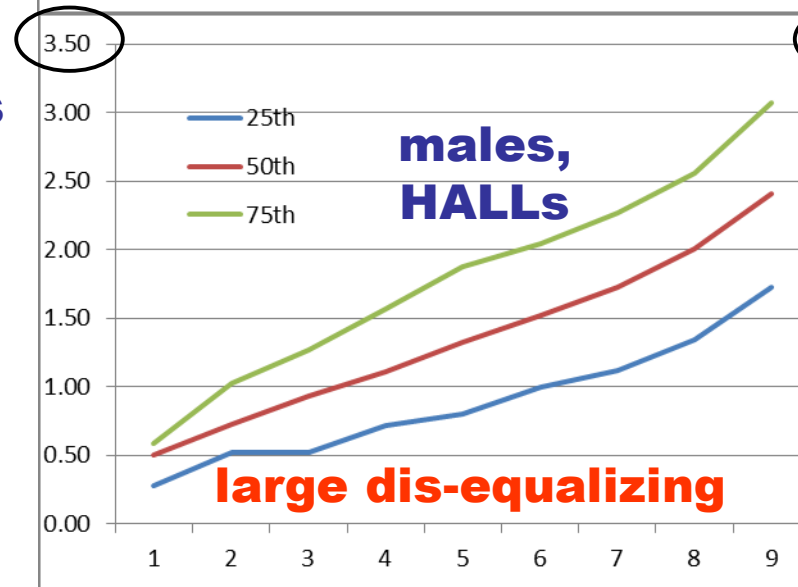
- moving everyone always to the top SES category over their lifetimes (university grad & top income decile) is associated with ~ 2 year and ~ 1 year increases in lifetime health (both LL and HALL) for men and women respectively
- for men, this improvement is fairly evenly spread throughout the lifetime health distribution, so generally neutral for univariate inequality
- for women, improving SES at the lowest levels of lifetime health has little impact; it is most important at the 3rd to 8th deciles of LL and HALL
- thus, having top SES for women is dis-equalizing, then flat, and then equalizing as one moves up women's lifetime health spectrum

No Pain Scenario Compared to Baseline

Δ LLs
years



Δ HALLs
years



horizontal axes: decile cut-points of the LL or HALL distributions

No Pain Scenario Compared to Baseline

- for both men and women, eliminating pain has almost no impact on LL, <0.2 years in most deciles for both men and women

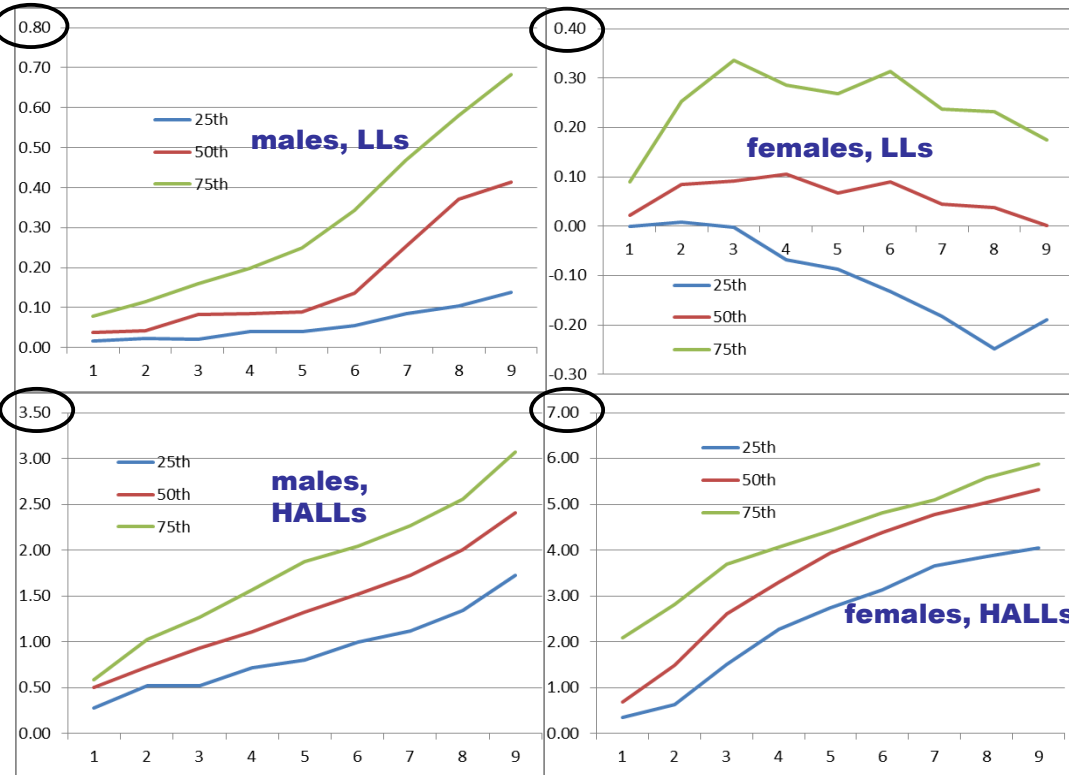
- pain has far larger impacts on HALLs: medians > ~4 years for women in most deciles of HALL and ~1 to 2 years for men

- for univariate health inequality, and for both men and women, the lower one's *lifetime* health, the smaller is the impact on HALL of eliminating pain

- intuition: poorer lifetime health is more often associated with other serious functional limitations, e.g. cognitive and mobility rather than pain

- i.e. eliminating pain is generally of greater benefit for those with better lifetime health

- hence, eliminating pain is highly *dis-equalizing*



horizontal axes: decile cut-points of the LL or HALL distributions

Concluding Comments

- focus has been on full lifecycle HALE as the key “bottom line” health indicator, beyond LE
- understanding impacts of health determinants requires more than piecemeal epidemiology
 - need a coherent network of estimated dynamic relationships embodied in a microsimulation model
- assessing “justness” of health inequalities entails using uni- not bivariate measures
- some surprising and counter-intuitive results
 - yes, eliminating smoking would be generally equalizing
 - improving SES generally neutral for men, disequalizing for women in poorer lifetime health
 - eliminating pain: small effects on LE, but large and highly disequalizing impacts on HALE, more for women