The Relationship between Socio-Economic Circumstances and Causal Mortality

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Plan

- Introduction
- Data
- Methodology
- Shocking Causal Mortality
- Preliminary Results
- Conclusions

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Introduction

- The motivation is to gain an improved understanding of mortality.
  ↳ Information is lost in aggregate mortality data . . .
  . . . Potentially found in causal mortality data!
- Reliable data is not readily available.
  ↳ Office for National Statistics data with socio-economic variables!
- What if circulatory-related deaths are considerably reduced?
  ↳ This scenario cannot be tested using aggregate models . . .
  . . . But it can be tested using causal models!
  ↳ Which socio-economic group stands to benefit most?
- Be careful! Causes are intrinsically dependent!
  ↳ Instantaneous probabilities vs. annual probabilities.
- Aim: quantify the impact on {residual} life expectancy.
  ↳ Study effects of scenarios on socio-economic gaps.

⇝ {This is a work-in-progress; feedback is most welcome!}

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Data

- The UK Office for National Statistics.
  - ↳ Data, by gender, for 1981–2007.
  - ↳ Five-year age groups, from 25–29, . . . , 80-84, and 85+.
  - ↳ Socio-economic circumstances in quintiles.
- Deaths categorized by the International Classification of Diseases.
  - ↳ When classifications change, comparability ratios are applied.
  - ↳ This is to maintain some consistency under classification shifts.
- Adjusted death rates are produced and analyzed.
  - ↳ Relevant exposure adjustments are also made.

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Multinomial Logistic Model

- Let $D_i(x,t)$ denote random deaths from cause i for age x at time t.
- Let $L(x,t)$ denote the subsequent survivors.
- Consider n causes.

$$Y(x,t) = (D_1(x,t), D_2(x,t), \ldots, D_n(x,t), L(x,t))'.$$

Assume $Y(x,t) \sim$ multinomial distribution $\{\pi(x,t),\ E(x,t)\}$, with

$$\pi(x,t) = \{q_1(x,t), q_2(x,t), \ldots, q_n(x,t), p(x,t)\}',$$

where,

$$\sum_{k=1}^{n} q_k(x,t) + p(x,t) = 1,$$

and

$$E(x,t) = L(x,t) + \sum_{k=1}^{n} D_k(x,t).$$

$\rightsquigarrow$ Annual probabilities and initial exposure.

Multinomial **Logistic** Model

- Adopt survival as the baseline category in the logistic framework.

$$\log \frac{q_i(x,t)}{p(x,t)} = X(x,t)\beta_i, \quad \text{for } i \in \{1,\ldots,n\}.$$

- $X(x,t)$ is the design matrix, and
- β_i the regression parameters suited to cause i.

The probabilities are given as follows:

$$\begin{aligned} q_i(x,t) &= \frac{\exp\{X(x,t)\beta_i\}}{1+\sum_k \exp\{X(x,t)\beta_k\}}, \quad \text{for } i \in \{1,\ldots,n\}, \\ p(x,t) &= \frac{1}{1+\sum_k \exp\{X(x,t)\beta_k\}}. \end{aligned}$$

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Multinomial Logistic **Model**

Models typically include some combination of age, period, and cohort.

⇝ Consider a gender specific model with main and interaction effects:

- Age is given by age-groups, which we treat categorically.
  - ↳ 13 groups: 25-29, 30-34, … 80-84, 85+.
- Period is treated continuously.
  - ↳ Continuous time avoids time-series consideration when forecasting.
- Cohort is excluded as a *main* effect:
  - ↳ We have a limited number of periods.
  - ↳ Causal mortality is more intuitively linked to period effects.
- Socio-economic circumstance quintiles are treated categorically.

- Age–period interaction is included!
  - ↳ "Lee-Carter" observation: age-groups have different time trends.
- Include socio-economic–age and –period interactions!

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The Regression Formula

$$
\begin{aligned}
\eta_i(g,x,s,t) \quad = \quad & \beta_{0,i} + \beta_{1,g,i} + \beta_{2,x,i} + \beta_{3,s,i} + \beta_{4,i}t \\
& + \beta_{5,g,x,i} + \beta_{6,g,s,i} + \beta_{7,g,i}t \\
& + \beta_{8,x,s,i} + \beta_{9,x,i}t + \beta_{10,s,i}t \\
& + \beta_{11,g,x,s,i} + \beta_{12,g,x,i}t + \beta_{13,g,s,i}t.
\end{aligned}
$$

where,

$$\eta_i(g,x,s,t) = \ln \frac{q_i(g,x,s,t)}{p(g,x,s,t)}.$$

Highlighted terms are gender-specific.

$\leadsto$ What remains is an intercept, three main and interaction effects.

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Cause Elimination

- Consider the elimination of cause j.
- The probabilities in our model are adjusted as follows:

$$\begin{aligned} q_j(x,t) &= 0, \\ q_i(x,t) &= \frac{\exp\{X(x,t)\beta_i\}}{1+\sum_{k\neq j}\exp\{X(x,t)\beta_k\}}, \quad i \neq j \\ p(x,t) &= \frac{1}{1+\sum_{k\neq j}\exp\{X(x,t)\beta_k\}}. \end{aligned}$$

- Representative of a proportional re-weighting of the probabilities.

⇝ This essentially ignores extrinsic dependence amongst the causes.
↳ {We are considering "multi-cause data" to address this!}

Shocking Causal Mortality

- In general, suppose we introduce a shock $\rho_i \geq 0$ to cause i.
  - Values of $\rho_i > 1$ signify a marginal increase in mortality.
  - The value $\rho_i = 0$ corresponds to cause elimination.
- The probabilities are adjusted as follows:

$$q_i(x,t) = \frac{\rho_i \exp\{X(x,t)\beta_i\}}{1 + \sum_k \rho_k \exp\{X(x,t)\beta_k\}},$$

$$p(x,t) = \frac{1}{1 + \sum_k \rho_k \exp\{X(x,t)\beta_k\}}.$$

- Based solely on $\rho_i > 0$, will $q_i(x,t)$ increase or decrease?
- Previous work has considered shocks on an instantaneous basis.
  - The annual approach re-distributes less probability to survival.

    ↳ It is more conservative in a mortality-sense.

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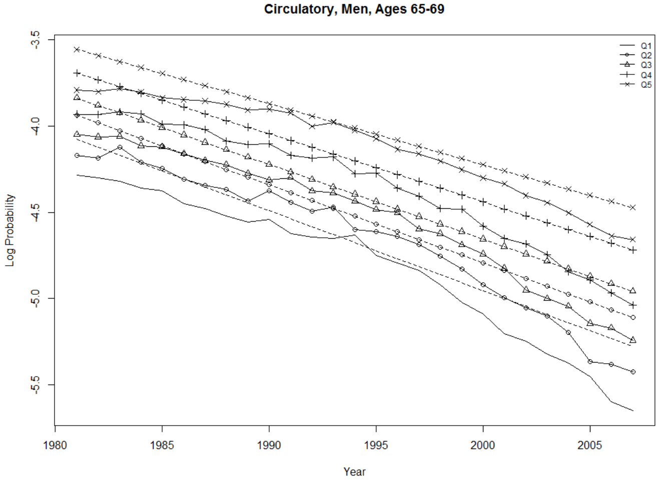
Analysis of Effects

Effect	DF	Wald Chi-Square	Pr > ChiSq
gender	6	34	< 0.0001
age	72	22012	< 0.0001
sec	24	3407	< 0.0001
year	6	486	< 0.0001
gender*age	72	5016	< 0.0001
gender*sec	24	556	< 0.0001
gender*year	6	36	< 0.0001
age*sec	288	70431	< 0.0001
age*year	72	23398	< 0.0001
sec*year	24	3668	< 0.0001
gender*age*sec	288	2818	< 0.0001
gender*age*year	72	4937	< 0.0001
gender*sec*year	24	557	< 0.0001

Fitting the data results in high significance for all effects!

↳ {sec = socio-economic circumstances}

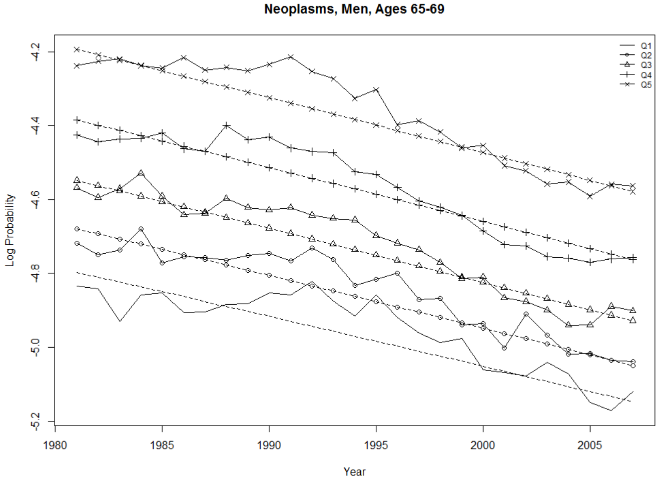
Observed and Fitted {log} Mortality



⇝ Overestimating mortality for this {and older} age-group!

↳ {Might have to consider quadratic time}

Observed and Fitted {log} Mortality



⇝ A pretty good fit, especially in the final year!
↳ {Linear time appears to suffice for this cause}

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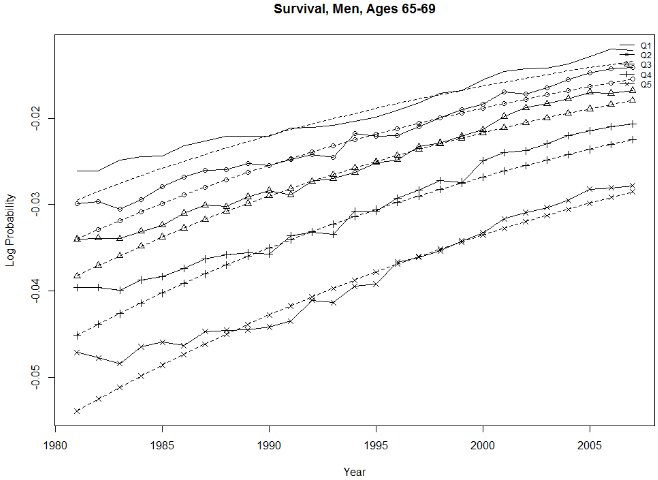
Observed and Fitted {log} Survival



⇝ Evidence of compression; especially at higher quintiles!

↳ {Again, notice underestimation of survival}

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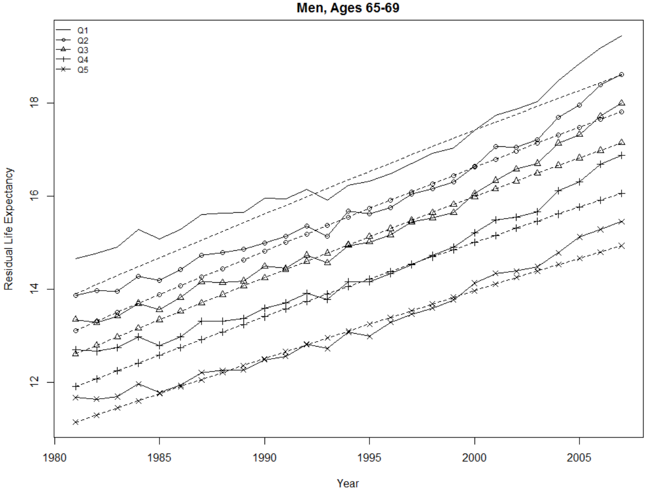
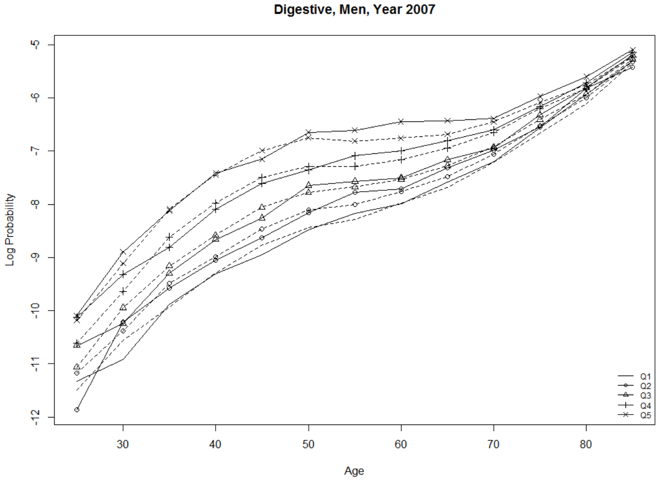
Observed and Fitted {Residual} Life Expectancy



⇝ Expansion in life expectancy?! {an aggregate measure!}

↳ {It captures the mortality expansion in later age-groups}

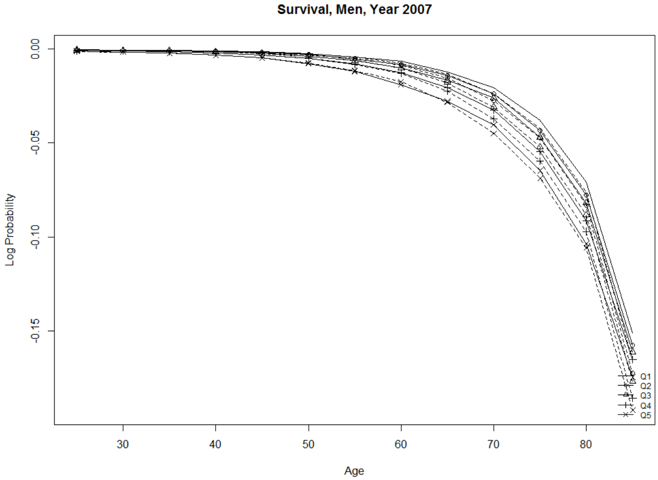
Observed and Fitted {log} Mortality



⇝ It looks like the role of 'sec' diminishes with age!

↳ {A difficult picture to digest, age-effect is dominating!}

Observed and Fitted {log} Survival



⇝ Survival plots tell a different tale. {Imperfect fit notwg!}
  ↳ {Of course, age-effect is, again, dominating.}

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Where we aim to go from here ...

What happens when a cause is shocked {eliminated}!
↳ What happens to life expectancy?

Again, consider 65 year-old male residual life expectancy:

Life Expectancy	Q1	Q2	Q3	Q4	Q5
Fitted	18.59	17.81	17.14	16.06	14.93
Fitted {– circulatory}	24.04	23.21	22.48	21.23	19.95
Gain	5.46	5.40	5.34	5.18	5.02

⇒ The most affluent benefit most from a 'positive' shock to circulatory.

Given an ability to shock causes, what criteria should be optimized?

- Reduce the socio-economic gap?
- Provide the biggest life expectancy gains for the population?
- Etc.

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