

Living to 100: Mortality Modelling

Modelling, Measurement and Management of Longevity Risk

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Society of Actuaries Annual Meeting, Boston, October 2017



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The 'Modelling, Measurement and Management of Longevity and Morbidity Risk' research programme is being funded by the ARC, the SoA and the CIA.

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ARC research program themes

- Improved models for mortality
- Key drivers of mortality
- Management of longevity risk
- Morbidity risk modelling for critical illness insurance

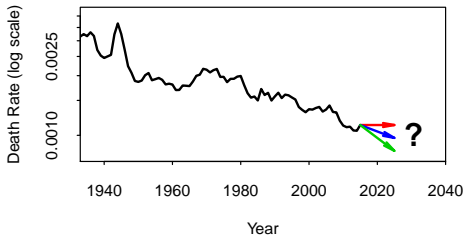
Outline

- Part 1: All cause mortality modelling
 - Introduction to stochastic mortality models
 - Why?
 - Example applications
- Part 2: Key drivers
 - Education level
 - Cause of death
 - Health inequalities

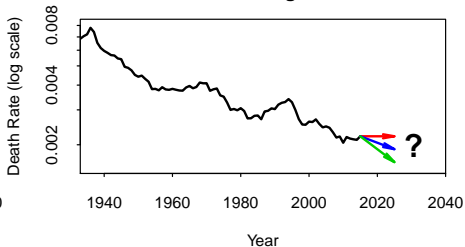
Part 1: All Cause Mortality Modelling

US Historical Death Rates

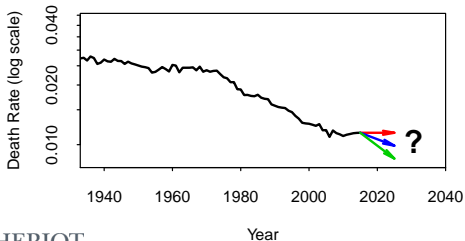
US Males Aged 20



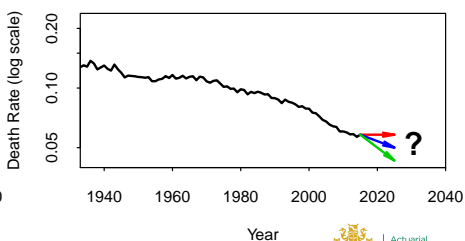
US Males Aged 40



US Males Aged 60



US Males Aged 80



Graphical Diagnostics

- Mortality is falling
- Different improvement rates at different ages
- Different improvement rates over different periods
- Improvements are random
 - Short term fluctuations
 - Long term trends
- All *stylised facts*
- Other countries:
 - Some similarities
 - Some different patterns

Why do we need stochastic mortality models?

Data \Rightarrow future mortality is **uncertain**

- Good risk management
- Setting risk reserves
- Regulatory capital requirements (e.g. Solvency II)
- Life insurance contracts with embedded options
- Pricing and hedging mortality-linked securities

Aims:

- to develop the **best models** for forecasting future uncertain mortality;
 - general desirable criteria
 - complexity of model \leftrightarrow complexity of problem;
 - **longevity** versus brevity risk;
- measurement of risk;
- valuation of future risky cashflows.

Aims:

- active management of mortality and longevity risk;
 - internal (e.g. product design; natural hedging)
 - over-the-counter deals (OTC)
 - securitisation
- part of overall package of good risk management.

Stochastic Mortality Models

Two basic examples:

- Lee-Carter Model (1992)
- Cairns-Blake-Dowd Model (CBD) (2006)

Stochastic model:

- Central forecast
- **Uncertainty around the central forecast**

Good ERM \Rightarrow Use a combination of stochastic projections *plus* some deterministic scenarios or stress tests

The Lee-Carter Model

Death rate:

$$m(t, x) = \frac{D(t, x)}{E(t, x)} = \frac{\text{deaths}(t, x)}{\text{average population}(t, x)}$$

Year t ; Age x .

$$\text{LC: } \log m(t, x) = \alpha(x) + \beta(x)\kappa(t)$$

- $\alpha(x)$ = base table; age effect
- $\beta(x)$ = age effect
- $\kappa(t)$ = period effect

The Lee-Carter Model

$$\log m(t, x) = \alpha(x) + \beta(x)\kappa(t)$$

- Estimate $\alpha(x)$, $\beta(x)$, $\kappa(t)$ from historical data
- “Traditional” model:
 - Fit a random walk model to historical $\kappa(t)$
 - Simulate future scenarios for $\kappa(t)$
 - Calculate future mortality scenarios given $\kappa(t)$
- Alternative models for $\kappa(t)$ can be used

The CBD Model

$q(t, x) =$ Probability of death in year t given initially exact age x .

$$q(t, x) \approx 1 - \exp[-m(t, x)]$$

$$\text{logit } q(t, x) = \log \left(\frac{q}{1 - q} \right) = \kappa_1(t) + \kappa_2(t)(x - \bar{x})$$

- $\kappa_1(t) =$ period effect; affects level
- $\kappa_2(t) =$ period effect; affects slope
- $\bar{x} =$ mean age
- Captures big picture at higher ages

Comparison

- LC \Rightarrow all mortality rates dependent on a single $\kappa(t)$
 \Rightarrow rates at all ages perfectly correlated
- CBD \Rightarrow simpler age effects (1 and $x - \bar{x}$)
but two period effects
 \Rightarrow richer correlation structure
- CBD linearity \Rightarrow
not good for younger ages
- Historical data:
Different improvements at different ages over different
time periods
 \Rightarrow need more than one period effect

Example: the Lee Carter Model

- (Applied to a synthetic dataset)
- $\log m(t, x) = \alpha(x) + \beta(x)\kappa(t)$
- Choose a time series model for $\kappa(t)$
- Calibrate the time series parameters using data up to the current time (time 0)
- Generate $j = 1, \dots, N$ stochastic scenarios of $\kappa(t)$

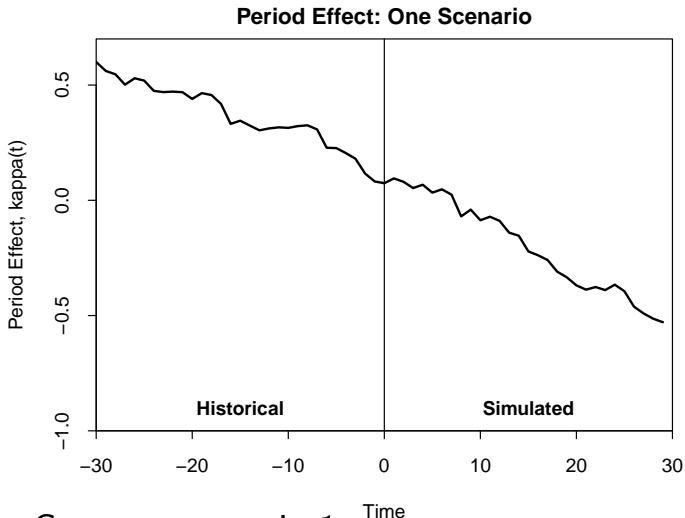
$$\kappa_1(t), \dots, \kappa_N(t)$$

Applications: Scenario Generation

- Generate N scenarios for the future $m(t, x)$
 $m_j(t, x)$ for $j = 1, \dots, N$, $t = 0, 1, 2, \dots$,
 $x = x_0, \dots, x_1$
- Generate N scenarios for the survivor index,
 $S_j(t, x)$
- Calculate financial functions

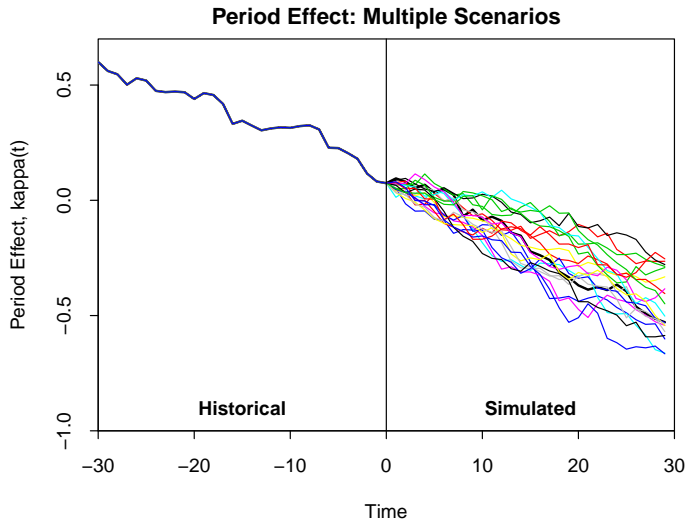
+ variations for some financial applications.

Applications: Scenario Generation, $\kappa(t)$

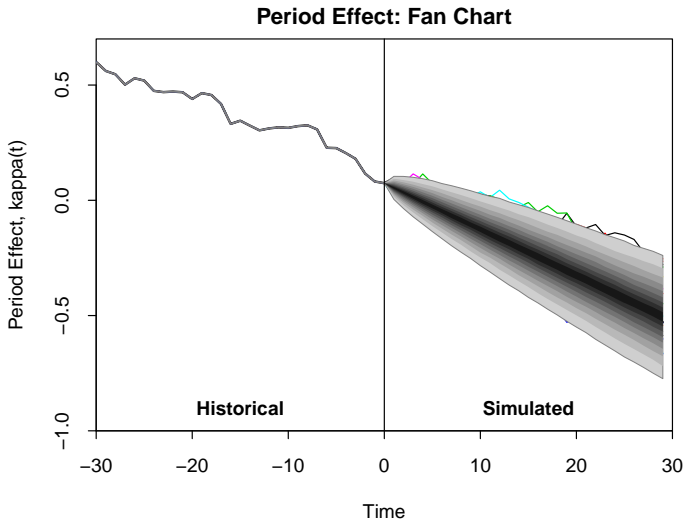


$\kappa(t)$: Generate scenario 1

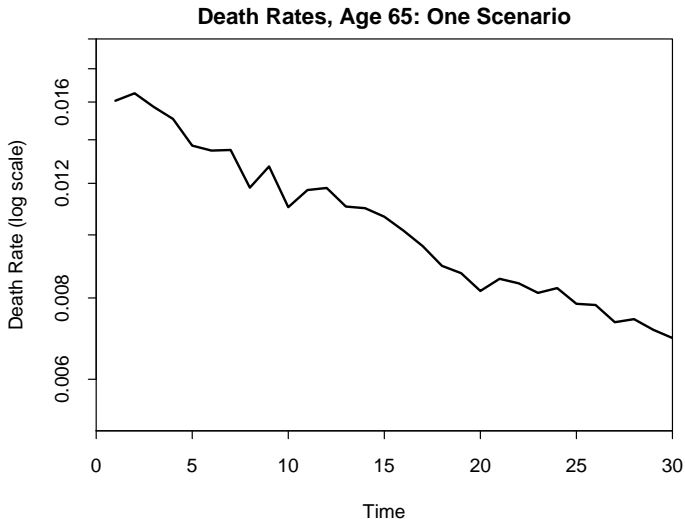
Applications: Scenario Generation, $\kappa(t)$



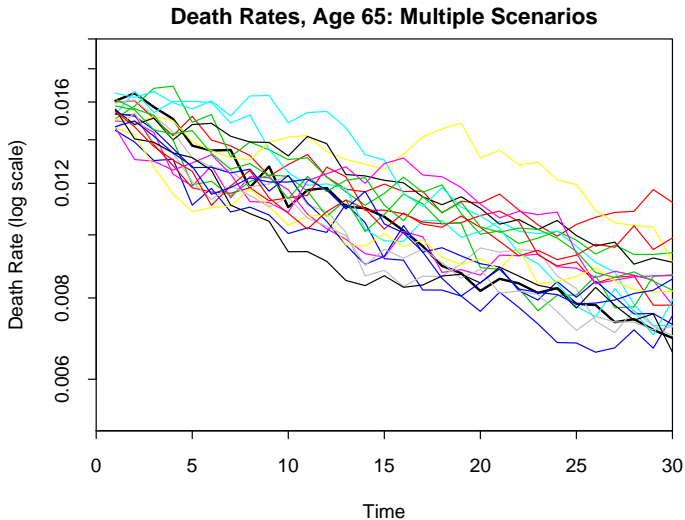
Applications: Scenario Generation, $\kappa(t)$



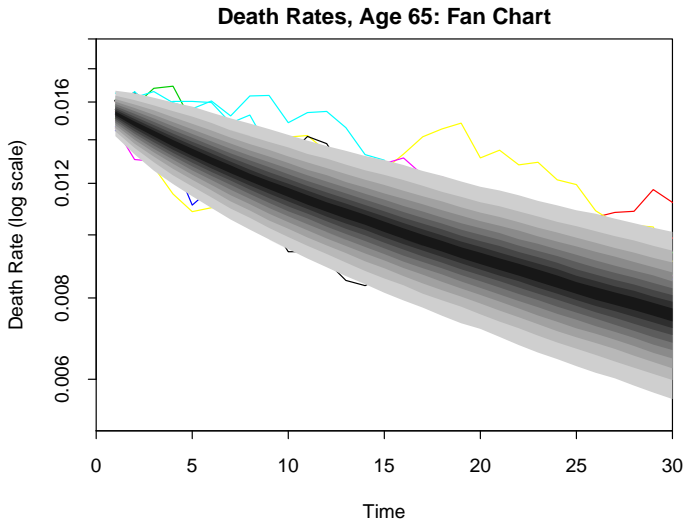
Applications: Scenario Generation, Future $m(t, x)$



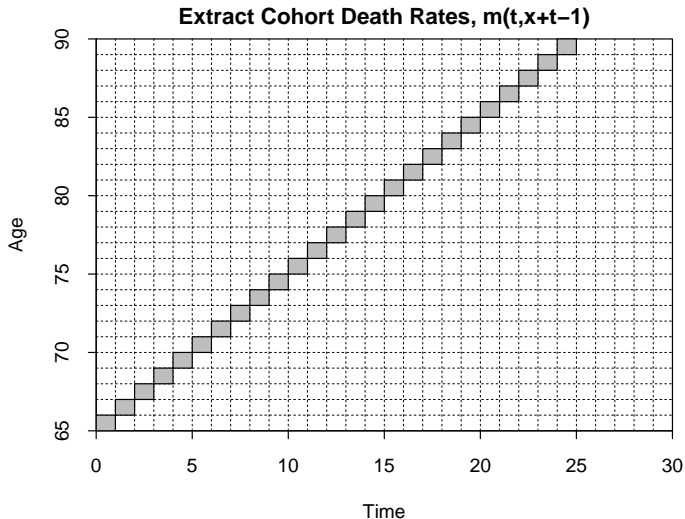
Applications: Scenario Generation, Future $m(t, x)$



Applications: Scenario Generation, Future $m(t, x)$



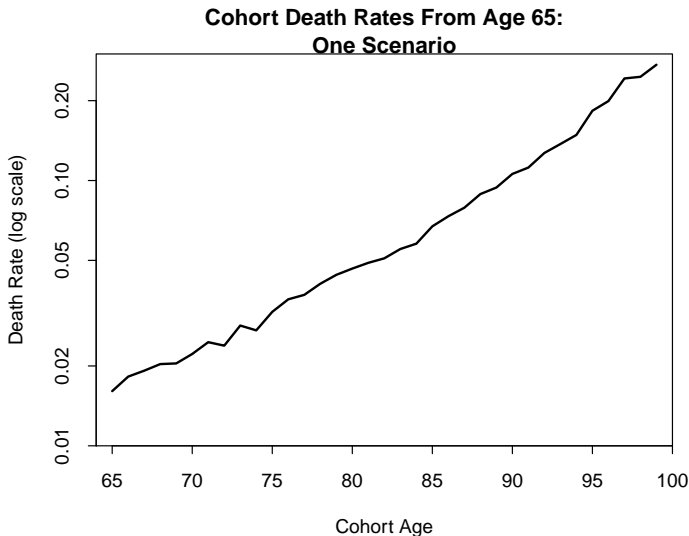
Annuity Pricing Requires Cohort Rates



Annuity valuation \Rightarrow follow cohorts

$m(0, x) \rightarrow m(1, x+1) \rightarrow m(2, x+2) \dots$

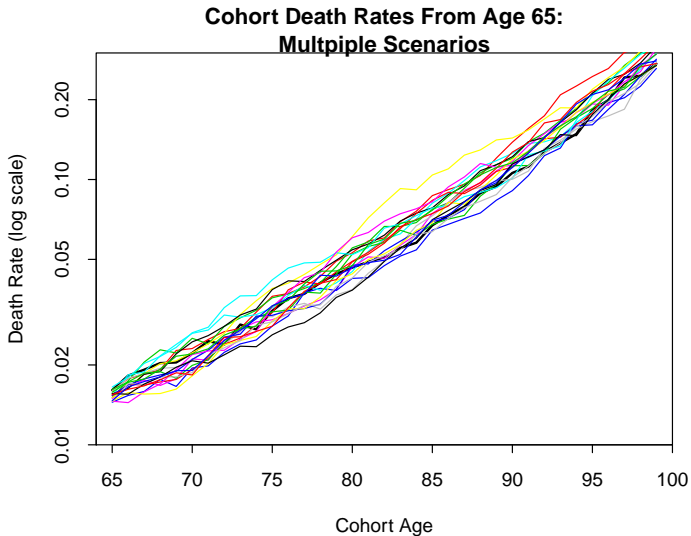
Annuity Pricing Requires Cohort Rates



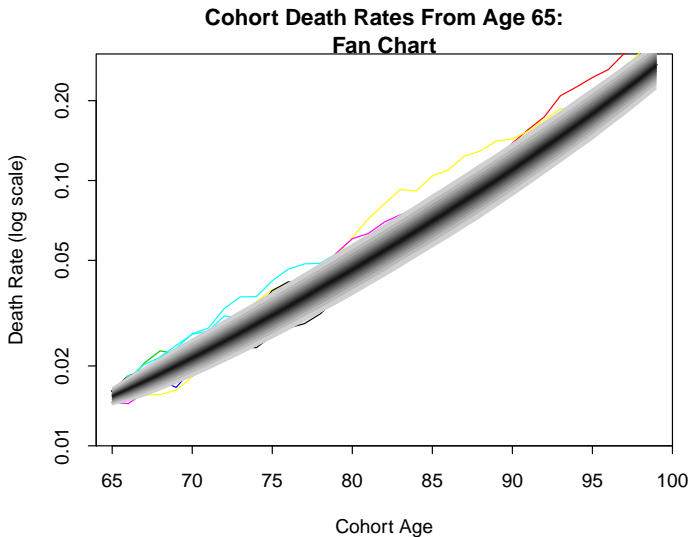
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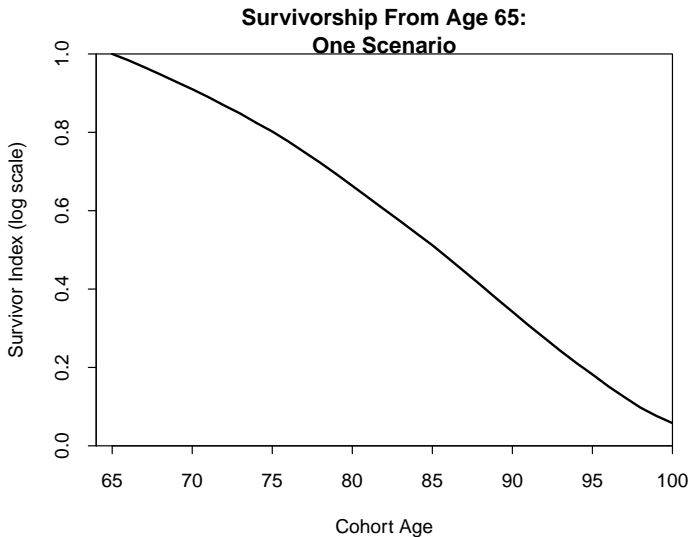
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Annuity Pricing Requires Cohort Rates

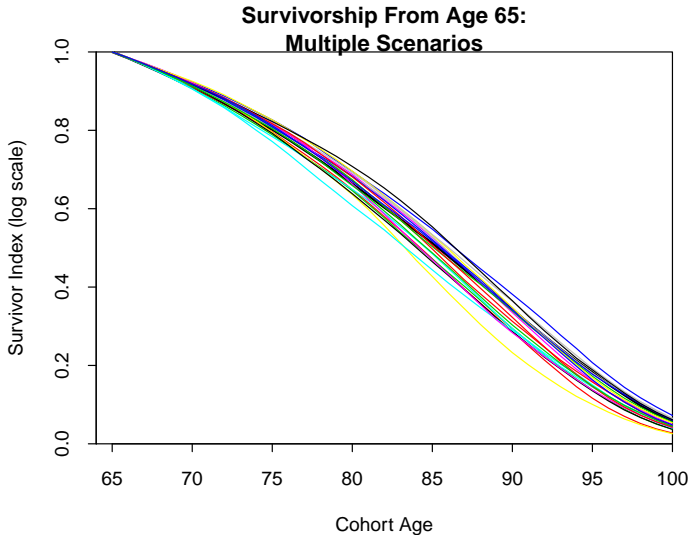


Cohort Survivor Index

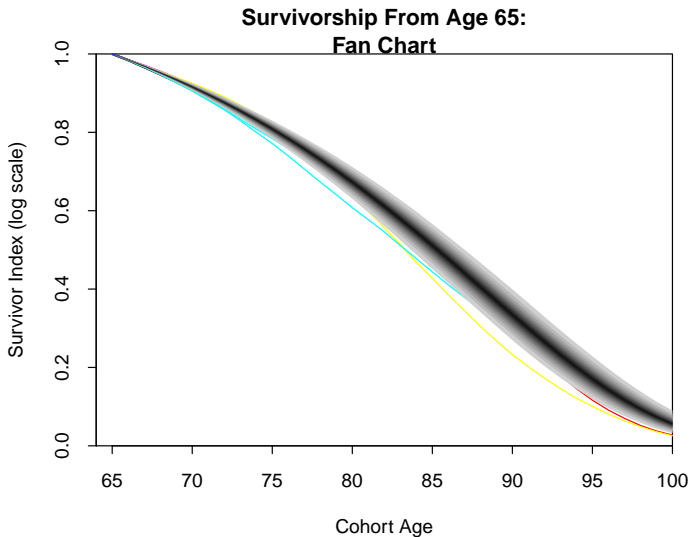


Cohort death rates \longrightarrow cohort survivorship

Cohort Survivor Index

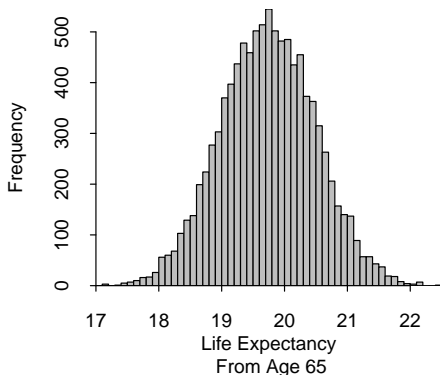


Cohort Survivor Index

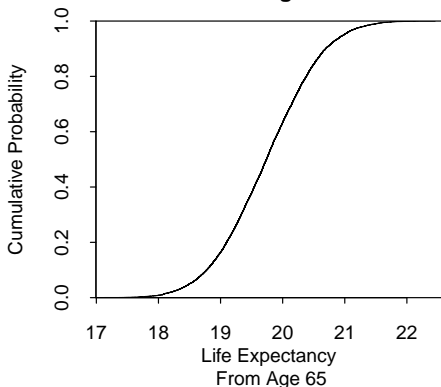


Life Expectancy

Cohort Life Expectancy
from Age 65



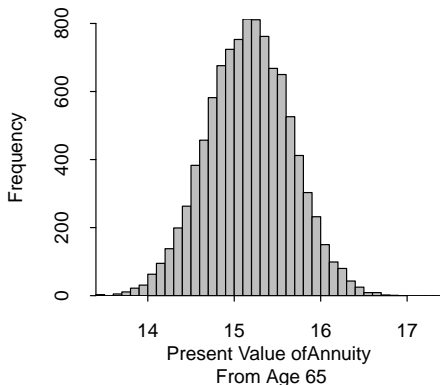
Cohort Life Expectancy
from Age 65



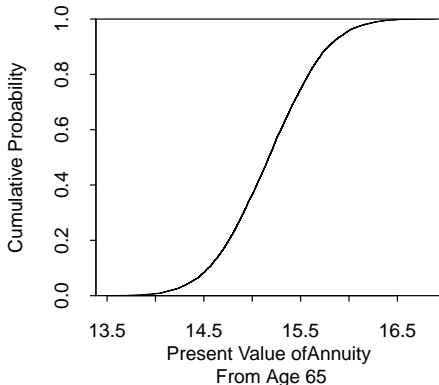
Cohort survivorship \rightarrow *ex post* cohort life expectancy
Equivalent to a continuous annuity with 0% interest

Annuity Reserving

Present Value of Annuity
from Age 65

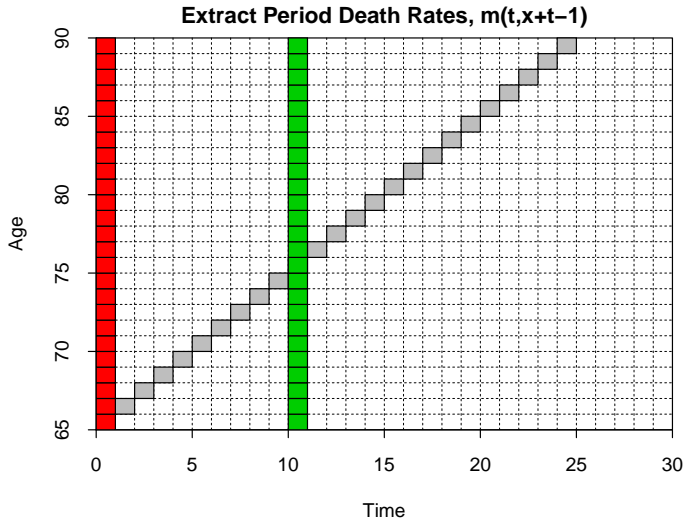


Present Value of Annuity
from Age 65

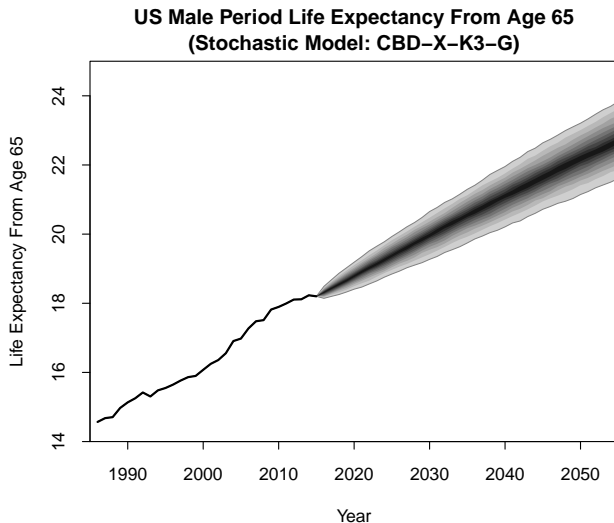


- Annuity of 1 per annum payable annually in arrears
- Interest rate: 2%

A Real Example: US Male Period Life Expectancy



A Real Example: US Male Period Life Expectancy



Mortality improvement rate $\approx 1.7\%$ p.a. at ages 65-85.

How to incorporate Expert Judgement?

- E.g. CBD model \Rightarrow
 - $m_{CBD}^j(t, x)$ scenarios
 - $\bar{m}_{CBD}(t, x)$ central forecast
- Expert judgement \Rightarrow
 - $\hat{m}(t, x)$ (central) forecast
- Blending \Rightarrow stochastic scenario j becomes

$$m^j(t, x) = \frac{m_{CBD}^j(t, x)}{\bar{m}_{CBD}(t, x)} \times \hat{m}(t, x)$$

- Fully stochastic \Rightarrow full risk assessment

How to incorporate Expert Judgement?

- A variation on this is required by UK life insurance regulators
- \Rightarrow Don't ignore stochastic models simply because you disagree with the central forecast!
- Additionally: new approaches to bring the two together are being developed

Part 2: Key Drivers

Drill into the Detail of US Data

- Level of **educational attainment** \Rightarrow predictor
- Individual **cause of death** \Rightarrow outcome

- Beware of grade inflation
- Help to understand trends in national data and subpopulations (e.g. white collar pension plan)



- Total Exposures: Human Mortality Database (smoothed to mitigate anomalies)
- CDC deaths: cause of death + education (+ ethnic group)
- CPS survey data: education proportions

Research \Rightarrow

- smart synthesis of three data sources
- improved, less noisy, exposures by education level



Purpose of looking at cause of death data

- What are the key drivers of all-cause mortality?
- How are the key drivers changing over time?
- Which causes of death have high levels of inequality:
 - by education
 - other predictors
- Insight into mortality underpinning life insurance and pensions
- Insight into potential future mortality improvements
- Beware of
 - changes in ICD classification of deaths (e.g. 1999)
 - drift in how deaths are classified
 - changing education levels (grade inflation)



Education Levels

Education

Low education	Primary and lower secondary education
Medium education	Upper secondary education
High education	Tertiary education



Cause of Death Groupings

1	Infectious diseases incl. tuberculosis	2	Cancer: mouth, gullet, stomach
3	Cancer: gut, rectum	4	Cancer: lung, larynx, ..
5	Cancer: breast	6	Cancer: uterus, cervix
7	Cancer: prostate, testicular	8	Cancer: bones, skin
9	Cancer: lymphatic, blood-forming tissue	10	Benign tumours
11	Diseases: blood	12	Diabetes
13	Mental illness	14	Meningitis + nervous system (Alzh.)
15	Blood pressure + rheumatic fever	16	Ischaemic heart diseases
17	Other heart diseases	18	Diseases: cerebrovascular
19	Diseases: circulatory	20	Diseases: lungs, breathing
21	Diseases: digestive	22	Diseases: urine, kidney,...
23	Diseases: skin, bone, tissue	24	Senility without mental illness
25	Road/other accidents	26	Other causes
27	Alcohol → liver disease	28	Suicide
29	Accidental Poisonings		

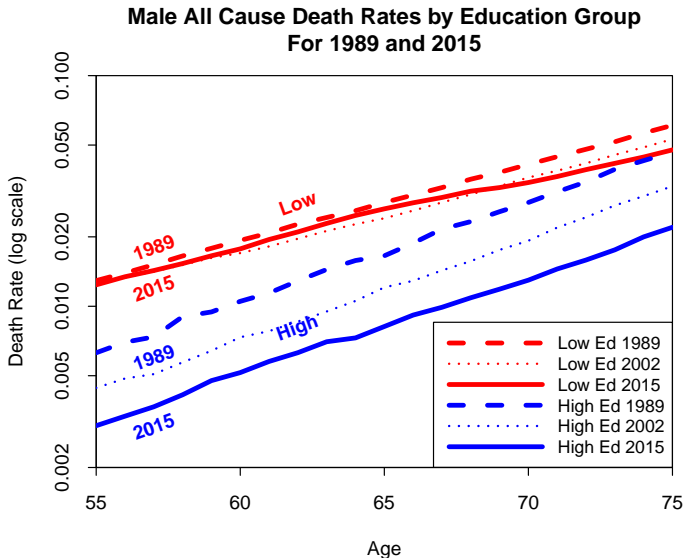


- Males and Females (2)
- Single ages 55-75 (21)
- Single years 1989-2015 (27)
- Causes of death (29)
- Low, medium & high education level (3)

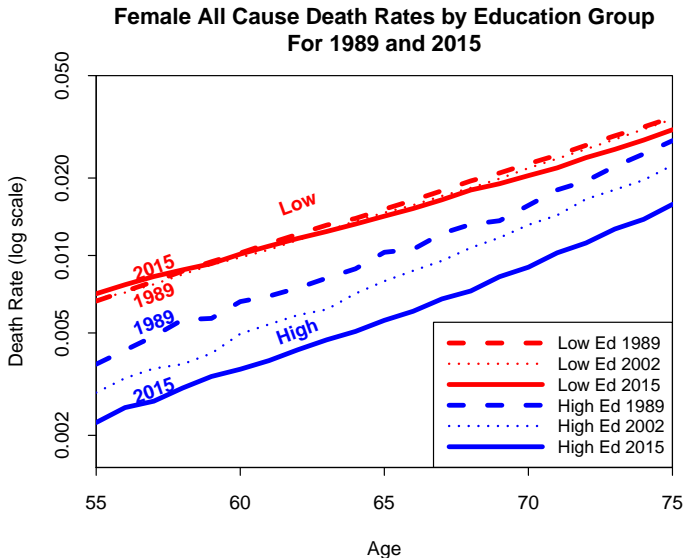
Note: HMD's *Human Cause of Death Database* \Rightarrow
All ages (5's), 1999-2015, No education



US Education Data: Growing Inequality, Males

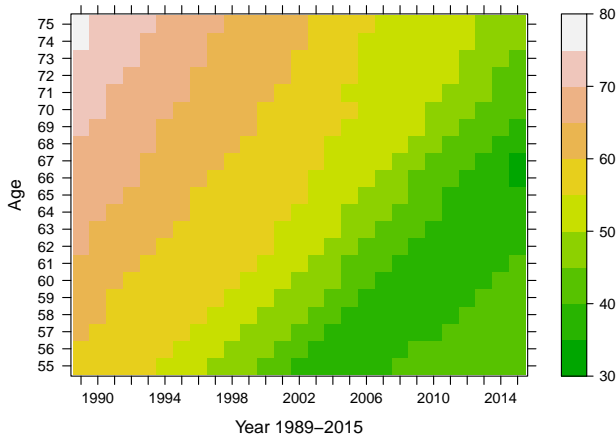


US Education Data: Growing Inequality, Females



Proportion of Males with Low Education

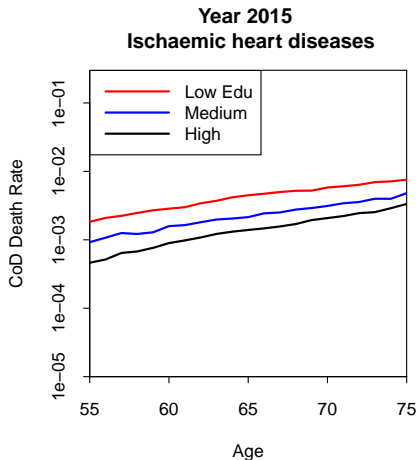
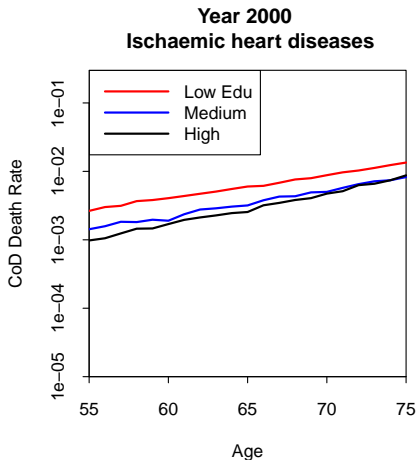
US Males 1989–2015 Ages 55–75:
Proportion of Population with Low Education



Cohort diagonals \Rightarrow *falling* percentage



US Education Data: CoD Death Rates

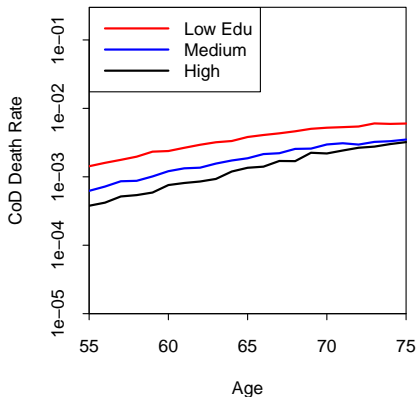


Widening gap

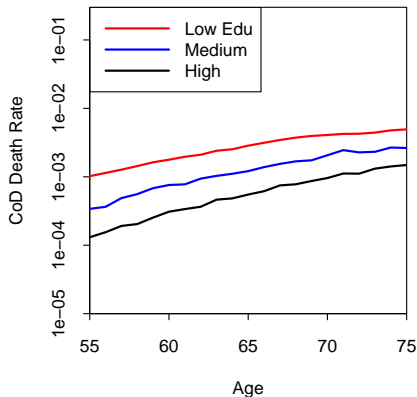


US Education Data: CoD Death Rates

Year 2000
Cancer: lung, larynx, ..



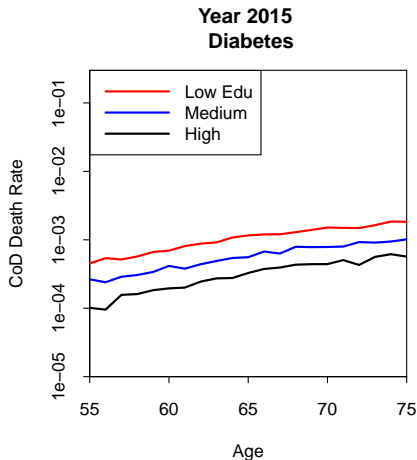
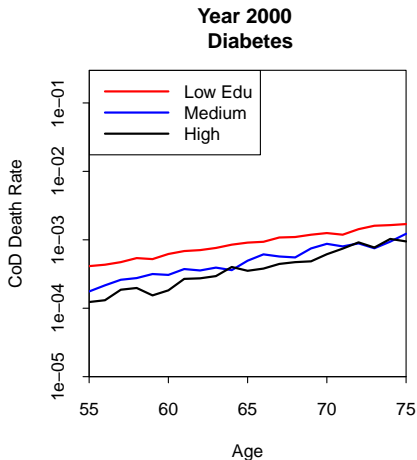
Year 2015
Cancer: lung, larynx, ..



Widening gap



US Education Data: CoD Death Rates

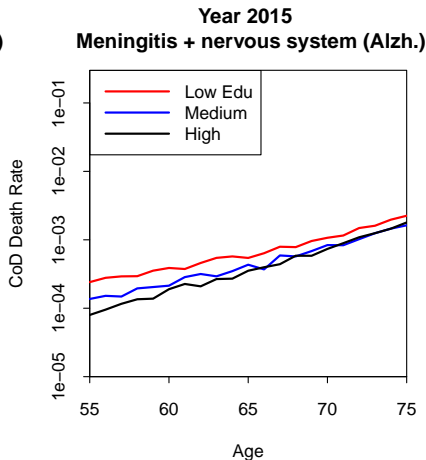
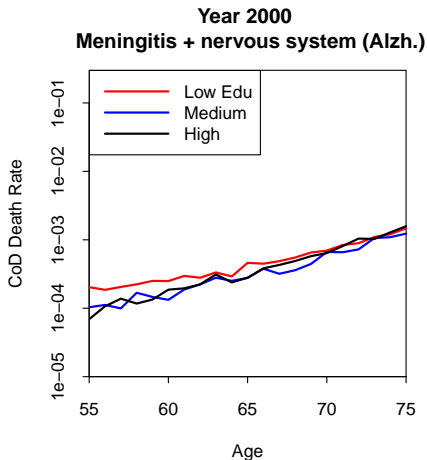


Widening gap;

Mixed improvements



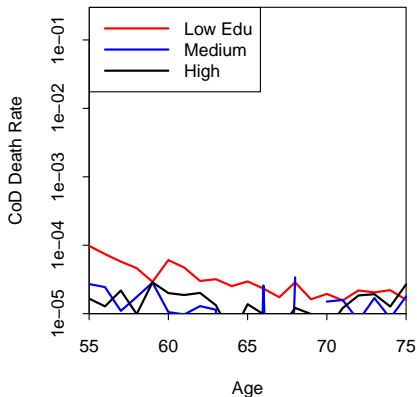
US Education Data: CoD Death Rates



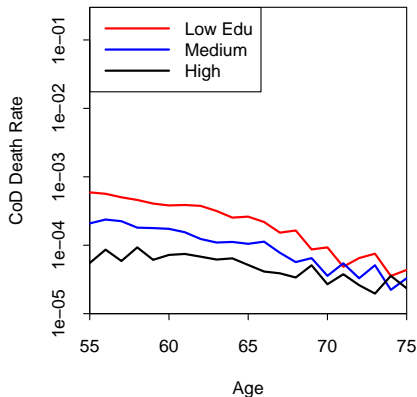
Widening gap; almost no improvements

US Education Data: CoD Death Rates

Year 2000
Accidental Poisonings



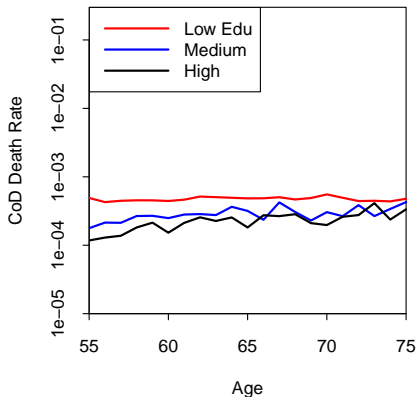
Year 2015
Accidental Poisonings



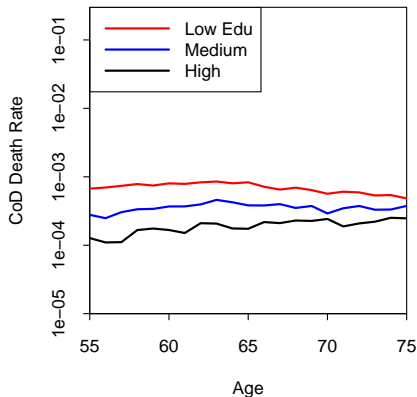
Case & Deaton (2015) \Rightarrow Accidental poisoning \nearrow

US Education Data: CoD Death Rates

Year 2000
Alcohol → liver



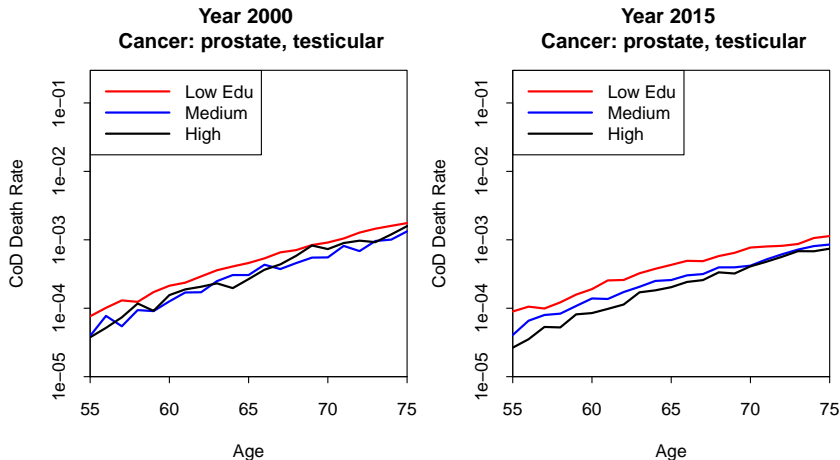
Year 2015
Alcohol → liver



Widening gap



US Education Data: CoD Death Rates



Denmark \Rightarrow almost NO gap by education;

Denmark \Rightarrow small gap by affluence; smaller than US by education

Cause of Death Data: Health Inequalities

- Some causes of death have **no obvious link** to lifestyle/affluence/education
e.g. Prostate Cancer
CancerUK: *Prostate cancer is not clearly linked to any preventable risk factors.*
- But education level \Rightarrow inequalities
- Possible explanations (a very non-expert view)
 - **onset is not dependent on lifestyle/affluence/education**
 - **BUT** lower educated \Rightarrow
 - ??? poorer health insurance coverage
 - ??? later diagnosis
 - ??? engage less well with treatment process
 - ??? lower quality housing/diet etc.



US Males: Low versus High Education

Do Low and High education groups have the same CoD rate?

- Four \times 5-year age groups
- 29 causes of death
- Signs Test (count low edu. $>$ high edu. mort.)
- $29 \times 4 = 116$ individual tests
- **Reject equality hypothesis *in all but one test***
- Accept H_0 ($p = 0.08$) for only one pairing:
Meningitis + nervous system (Alzh.), 70-74
- Most p -values $< 10^{-6}$



Summary

- Future work
 - Analysis of sub-national datasets
 - e.g. SoA Group and Individual Annuity data
 - e.g. individual pension plan data
 - Multiple population modelling

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Thank You!

Questions?

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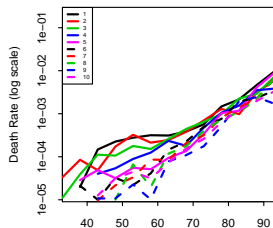
Discussion Point

- Medicare kicks in after age 65
- But no obvious impact on inequality gap
- Although inequality gap naturally narrows with age

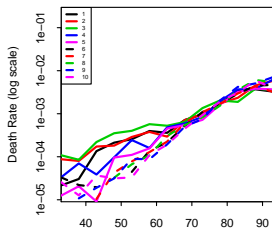


CoD Death Rates: Different Shapes & Patterns

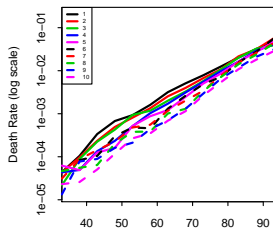
Infectious diseases incl. tuberculosi



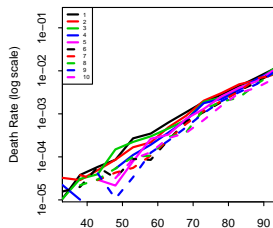
Meningitis + nervous system (Alzh.)



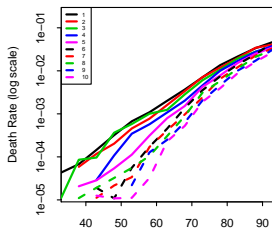
Ischaemic heart diseases



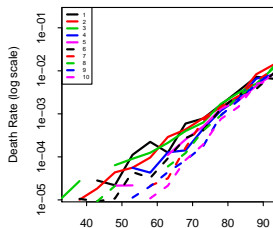
Diseases: circulatory



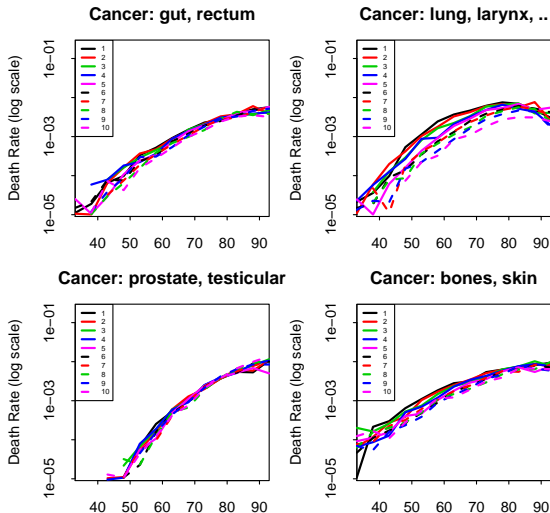
Diseases: lungs, breathing



Diseases: urine, kidney,...



CoD Death Rates: Different Shapes & Patterns



Shapes: Conclusions

- Typically:
 - Non-cancerous diseases \Rightarrow approximately **exponential** growth
 - Neoplasms (cancers) \Rightarrow **subexponential ???**
polynomial
- What does this reveal about different disease mechanisms?

