

Modelling Post-pandemic Mortality

Structural trend changes or extreme shocks?

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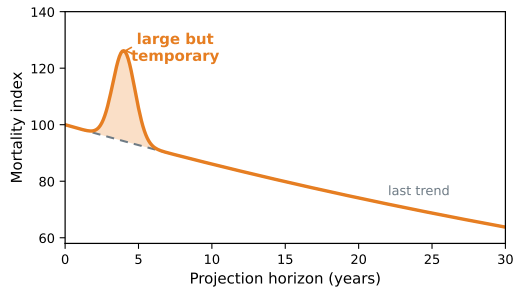
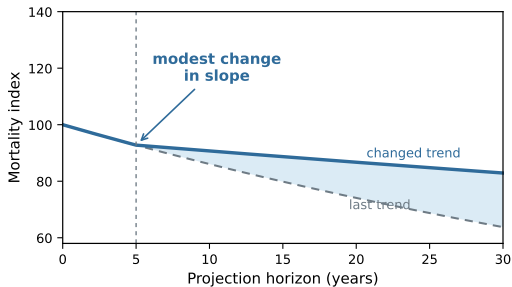
The School of Risk and Actuarial Studies, UNSW Sydney

joint work with Xiaochuan Lu, Daniel Meier and Andrés M. Villegas

Funding from:

Exploring trends in mortality improvements:
COVID-19, excess mortality, future outlook – Swiss Re

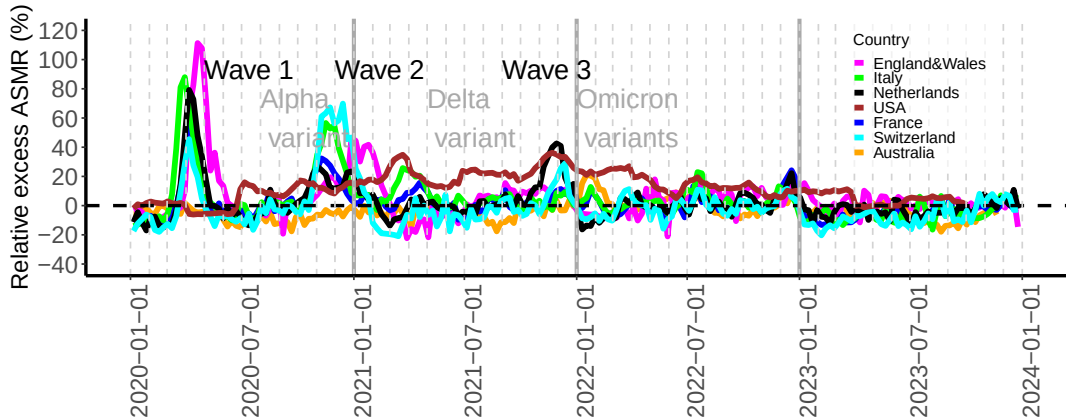
What matters more?



- How to treat extreme mortality shocks: outliers, temporary deviations, or evidence of a new trend?
- What to expect after a large shock —¹ reversion to trend, or a lasting shift?
- Which matters more for long-term mortality projections: extreme shocks or structural trend changes?

¹“All m-dashes in these slides were human generated.” — Terence Tao

Age-standardised mortality rates (ASMR) in COVID years



- Relative excess ASMRs, men, ages 0–85+, compared to 2015–2019
- How heavy can the tail of short-term mortality deviations be?
- Has the underlying pace of mortality improvement changed persistently?

Then what? Separate the risks before projecting them

- Develop evidence-based models for post-COVID mortality
 - ... extending age-period-cohort-improvement (APCI) type models
 - ... adding structural trend changes
 - ... clarifying the role of each term
- Revisit mortality modelling assumptions
 - ... disentangling trend vs. shock contributions across horizons
 - ... reflecting emerging post-pandemic patterns

HMD Data: 48 country-sex populations

Death Registrations and Population Estimates:

- All-cause deaths
- Country

Austria, Australia, Belgium, Bulgaria, Canada, Switzerland, Czechia, Denmark, Spain, Finland, France, England and Wales, Scotland, Northern Ireland, Ireland, Italy, Japan, the Netherlands, New Zealand, Norway, Portugal, Slovakia, Sweden, and the United States (USA)

- Sex
- Single ages (20-100)
- Single years (1950–2021)

How to improve APCI models: A trend-break extension

The mortality rate, $m_{x,t}$, structure for age x and year t :

$$\log(m_{x,t}) = \alpha_x + d_x(t - \bar{t}) + \sum_{j=1}^M d_x^{(j)}(t - \tau_j)^+ + \kappa_t + \gamma_{t-x}$$

for $(t - \tau_j)^+ = \max(0, t - \tau_j)$.

The equivalent improvement rate structure:

$$l_{x,t} = \underbrace{\tilde{l}_x}_{\text{Long-term improvement rate}} + \underbrace{\sum_{j=0}^M \tilde{l}_x^{(j)} \mathbb{1}(\tau_j < t \leq \tau_{j+1})}_{\text{Temporal deviations}} + \underbrace{\Delta \kappa_t}_{\text{Period shocks}} + \underbrace{\Delta \gamma_{t-x}}_{\text{Cohort effects}}$$

where $l_{x,t} = -\Delta \log(m_{x,t})$, $\tilde{l}_x^{(0)} = -d_x - \tilde{l}_x$, $\tilde{l}_x^{(j)} = -\left(d_x + \sum_{i=1}^j d_x^{(i)}\right) - \tilde{l}_x$ for $j = 1, \dots, M$.

How to calibrate APCI model with trend-breaks?

Step 1: Fit an APCI model with no breakpoints:

$$\log(m_{x,t}) = \alpha_x + d_x(t - \bar{t}) + \kappa_t + \gamma_{t-x}$$

Step 2: Identify potential trend breakpoints in κ_t

by examining structural changes

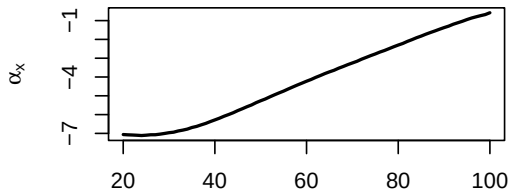
Step 3: Refit the APCI model allowing for identified breakpoints

Step 4: Reparameterise the model such that:

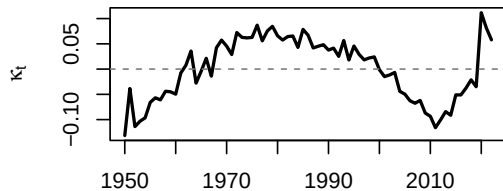
- d_x represents the long-term trend
- $d^{(i)}$ captures segment-specific deviations
- κ_t shows random shocks

Step 1: APCI model for men in England and Wales

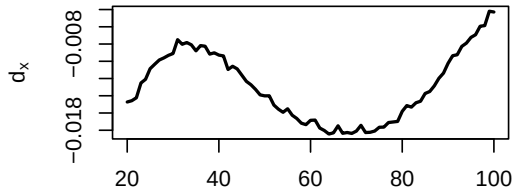
Age effect



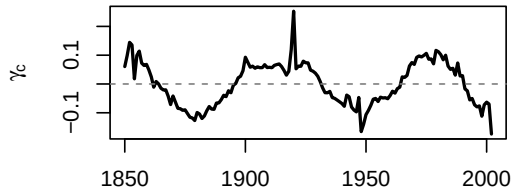
Period effect



Age-specific linear trend



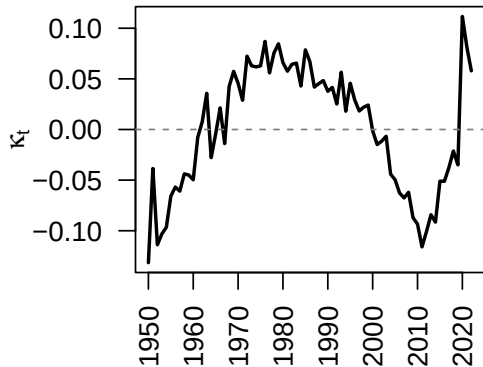
Cohort effect



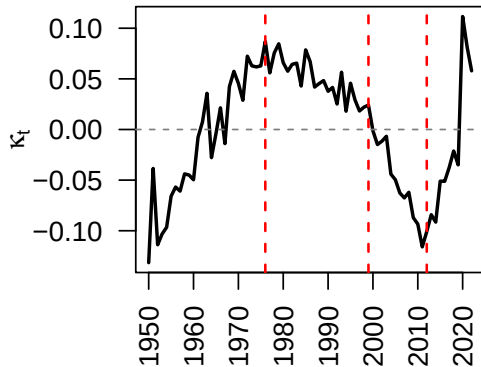
Cohort (year of birth)

Step 2: Detecting Trend Breaks in κ_t

No breakpoints



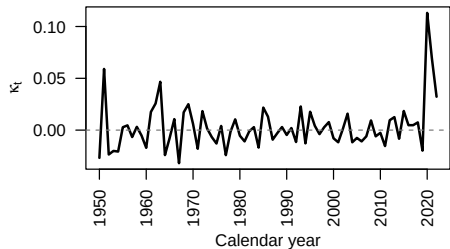
With breakpoints



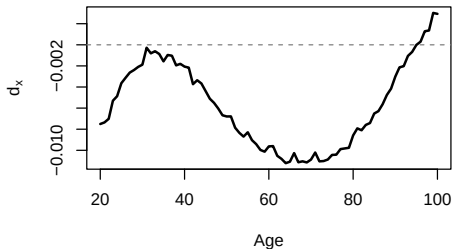
- Breakpoints in 1976, 1999, and 2012

Step 3 and Step 4: Fit APCI model with trend breaks

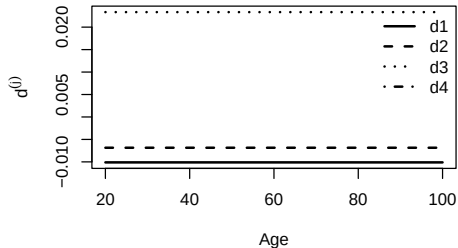
Reparameterised period effect



Reparameterised age-specific linear trend

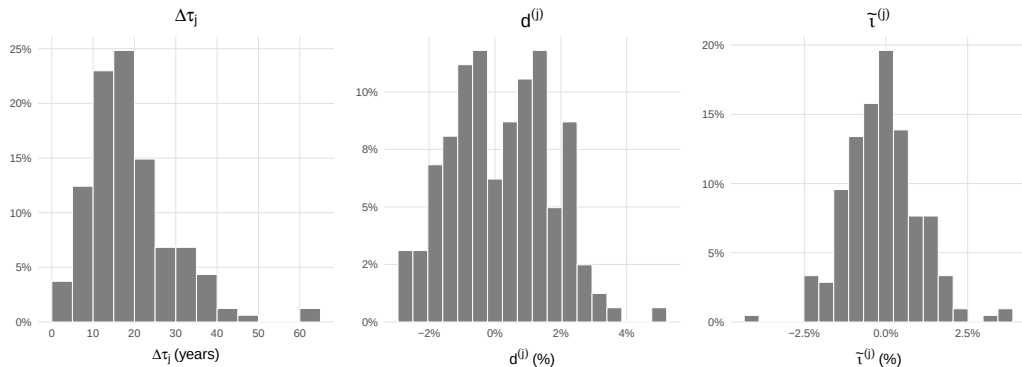


Trend breaks



- d_x : Long-term trend
- d^j : Segment deviations
- κ_t : Short-term shocks

Calibrating future trend changes from 48 populations



- Empirical distributions of $\tilde{\tau}^j$ (improvement-rate temporal deviation), $\Delta\tau_j$ (trend-change duration), d^j (trend-change increment)

Future trend changes: when and how large?

When does the next change occur? How large is the next deviation?

Exponential: $\lambda = 0.0554$, mean wait 18.0 years.

Gamma: $\alpha = 3.84$, $\lambda = 0.182$, mean wait 21.1 years.

Gamma fits better (AIC/BIC); Exponential kept as a transparent benchmark.

$$\tilde{t}_{rj} = \mu_{g_r} + \varepsilon_{rj}, \quad \varepsilon_{rj} = \phi \varepsilon_{r,j-1} + u_{rj}$$

$\phi = -0.436$, residual s.d. = 0.0151 $\Rightarrow$ mean-reverting deviations.

Calibrating shock risk: one light- and two heavy-tailed methods

Gaussian

Parsimonious benchmark.
Symmetric and light-tailed.

Normal-Inverse Gaussian

Allows skewness and heavier tails while retaining finite moments.

POT-GPD

Models the upper tail separately and targets extreme mortality shocks directly.

Male population	Gaussian variance	NIG variance	POT tail shape
England and Wales	0.0005	0.0121	0.461 – finite variance
USA	0.0012	0.1131	1.700 – mean/variance not finite

England and Wales and the USA: baseline illustration

England and Wales, men

- Data: 1950–2021
- Breaks: 1976, 1999, 2012
- Latest regime deviation: -1.44%
- Lower Gaussian shock variance: 0.0005
- Last regime implies a marked slowdown in mortality improvement.

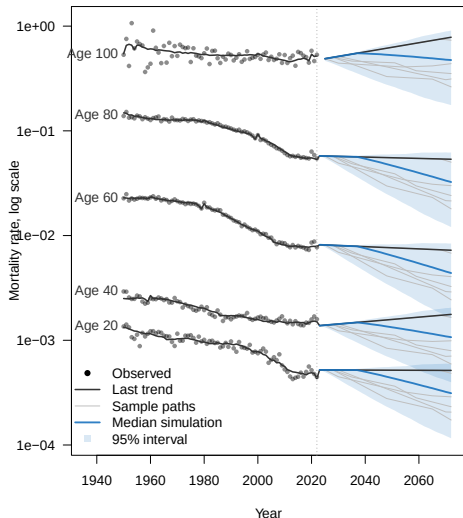
USA, men

- Data: 1950–2021
- Six breaks, latest at 2019.
- Latest regime deviation: -0.53%
- Higher Gaussian shock variance: 0.0012
- COVID shock is larger, but the latest slowdown is milder.

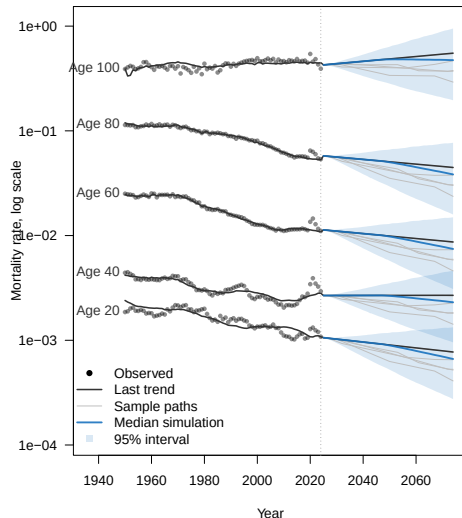
Baseline results use 10,000 paths, Exponential trend-change timing, AR(1) regime sizes, Gaussian shocks, and zero effects for new unobserved cohorts.

An illustration of future mortality for men

England and Wales Male – no cohort, no period shocks



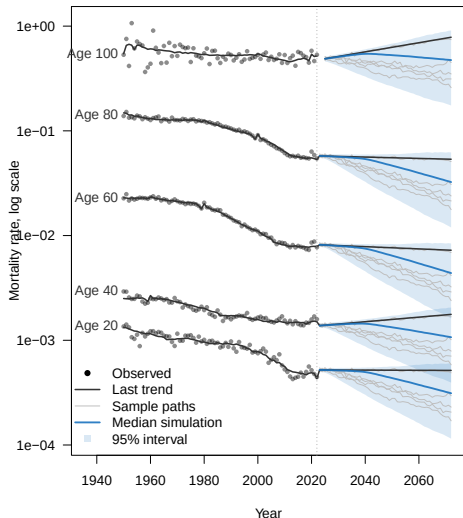
USA Male – no cohort, no period shocks



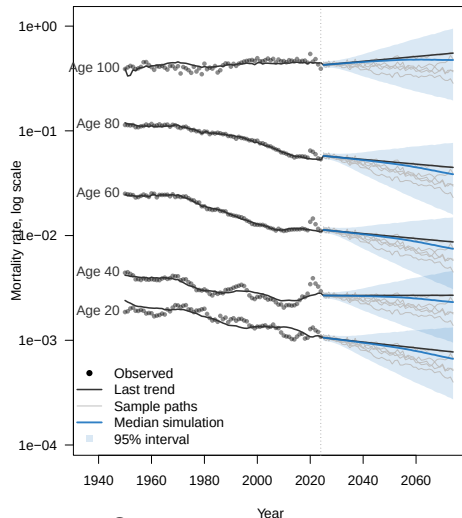
Long-term + Deviations

An illustration of future mortality for men

England and Wales Male – no cohort, with period shocks



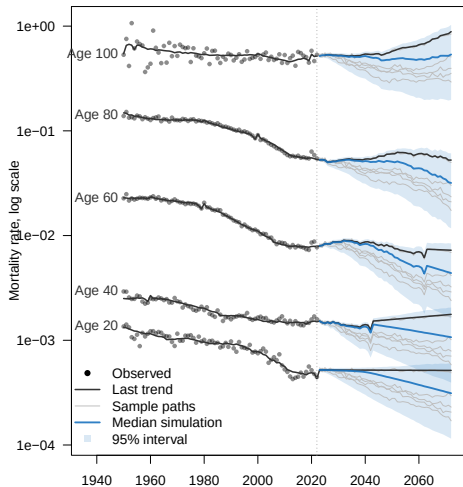
USA Male – no cohort, with period shocks



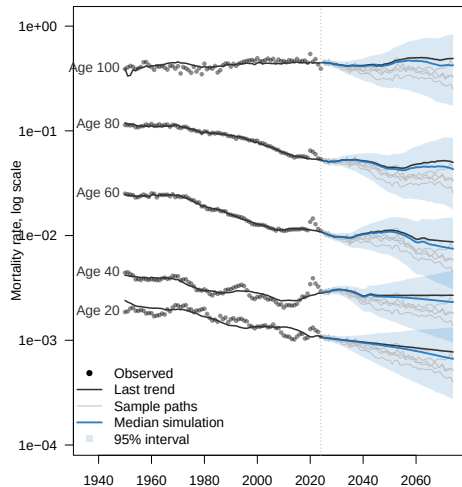
Long-term + Deviations + Shocks

An illustration of future mortality for men

England and Wales Male – with cohort and period shocks



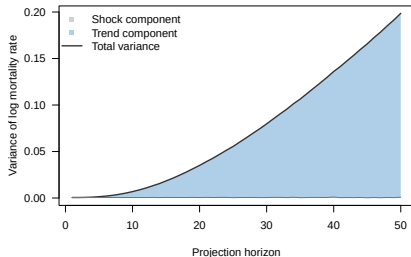
USA Male – with cohort and period shocks



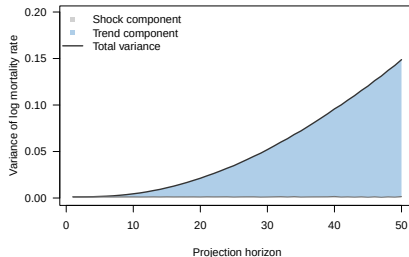
Long-term + Deviations + Shocks + Cohort

The dominant uncertainty changes with horizon

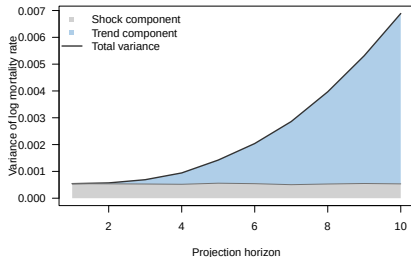
England and Wales Male – variance decomposition, h=50



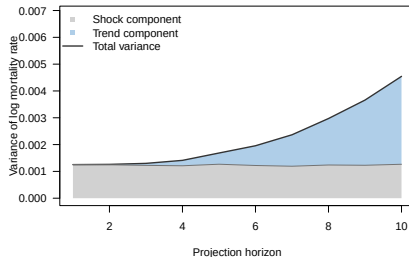
USA Male – variance decomposition, h=50



England and Wales Male – variance decomposition, h=10



USA Male – variance decomposition, h=10



- England and Wales has greater trend uncertainty; the USA has greater shock uncertainty.
- h shows projection horizon.

Discussion points

- An intuitive methodology consistent with established APCI practice
- Empirical findings from 48 country-sex populations
- Transparent and auditable decomposition
- Flexible shock-tail assumptions
- Implemented in the open-source trendMoMo R package
- Coherent multi-population dynamics?
- Age-specific trend changes?
- Stochastic future cohort process?

Thank you!

Questions?

The open-source trendMoMo R package: *github.com/amvillegas/trendMoMo*

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