

A Flexible and Robust Approach to Modelling Single Population Mortality

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Outline

- Motivation
- Model fitting
- Flexibility in mortality forecasting
- Bring closer industry practice and academic techniques

Two strands of work in progress:

- 1: Can the model fitting process be simplified and made more robust?
- 2: *In practice*: Disconnect between central forecasts of mortality and models to assess uncertainty. Can we pull these together?

⇒ How to make stochastic mortality models more useable?



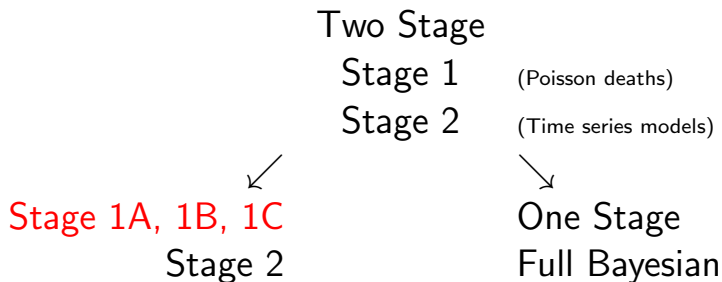
Simplify the model fitting process

- Problem: interacting age, period and cohort effects
 - ⇒ identifiability problems
 - ⇒ arbitrary constraints
- If period and cohort effects are *random walks*
 - ⇒ no problem
- Otherwise choice of constraints makes a difference.



Simplify/break down the model fitting process

Potential fitting algorithms



Example: A CBD-X Model

$$\log m(t, x) = \alpha(x) + \sum_{k=1}^3 \beta_k(x) \kappa_k(t) + \gamma(t - x)$$

where $\alpha(x)$ = non-parametric age effect

$$\beta_1(x) = 1 \quad \forall x$$

$$\beta_2(x) = (x - \bar{x})$$

$$\beta_3(x) = (x - \bar{x})^2 - \sigma_x^2$$

$\kappa_k(t)$ = period effects

$\gamma(c)$ = cohort effect.

(Variation on Plat (2009, IME). Also see Hunt & Blake (2014, NAAJ).)
Suitable for a wider age range than CBD-M7.

Simplify/break down the model fitting process

$$\log m(t, x) = \alpha(x) + \sum_{k=1}^3 \beta_k(x) \kappa_k(t) + \gamma(t - x)$$

- 1A: Estimate the base table, $\alpha(x)$
- 1B: Estimate the period effects, $\kappa_k(t)$, given $\alpha(x)$
- 1C: Estimate the cohort effect, $\gamma(c)$ given $\alpha(x), \kappa_1(t), \kappa_2(t), \kappa_3(t)$



Cons:

- Not the perfect maximum likelihood
- Less good for small populations

Pros:

- Flexibility over how to calibrate $\alpha(x)$ (e.g. Lee & Miller, 2001)
- Can apply smoothing
- No identifiability problems
- Robust
- Enough period effects \Rightarrow
 $\gamma(c)$ = small residual effects *with a distinct pattern* (*)
(Hunt & Blake, 2014)
(*) No pattern/very random \Rightarrow overfitting.
- Can import external $\tilde{\gamma}(c)$.
(Then fit $\alpha(x)$ given $\tilde{\gamma}(c)$ etc.)

How to bring industry practice and academic approach together?



CMI: UK Continuous Mortality Investigation

Chart 4A: Mortality improvements (male)

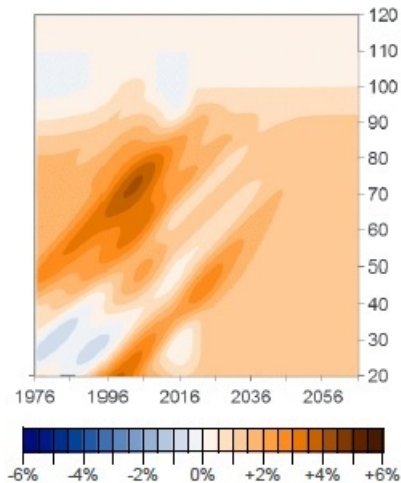
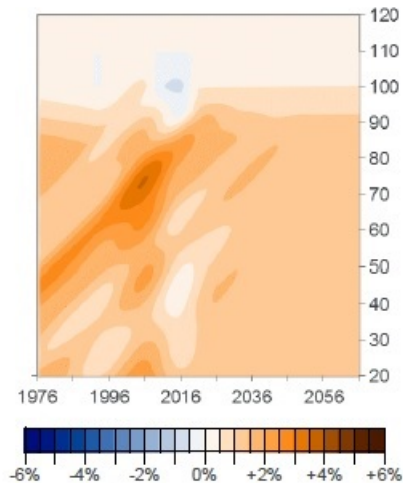


Chart 4B: Mortality improvements (female)



Source: CMI Working Paper 97

- Central forecast only
- Potentially lots of subjective inputs
 - Long term improvement rate (*)
 - Convergence period
- Default settings, but must set
 - Long term *flat* improvement rate
 - Base table



$$\log m(t, x) = \alpha(x) + \beta(x)(t - \bar{t}) + \kappa(t) + \gamma(t - x)$$

$\alpha(x), \beta(x)$ = non-parametric age effects

Optimise:

- Poisson log-likelihood; minus
- **penalty** for lack of smoothness in $\alpha(x), \beta(x), \kappa(t)$ and $\gamma(t - x)$

Smoothness \Rightarrow smooth heat map

CMI Heat Map

Chart 4A: Mortality improvements (male)

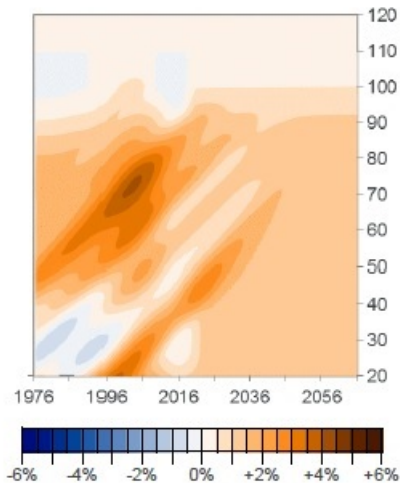
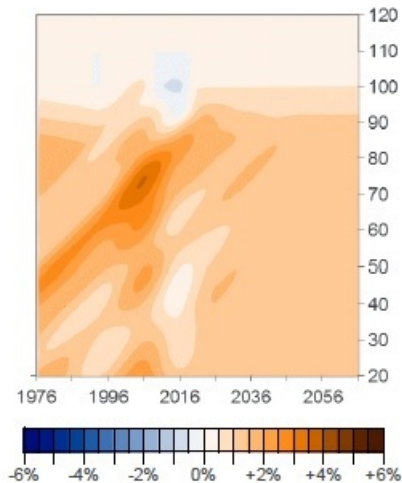


Chart 4B: Mortality improvements (female)



Source: CMI Working Paper 97

CMI (2016) mortality improvements

$$\log m(t, x) = \alpha(x) + \beta(x)(t - \bar{t}) + \kappa(t) + \gamma(t - x)$$

Historical improvement rate up to time T :

$$MI(t, x) = -\beta(x) - \left(\kappa(t) - \kappa(t-1) \right) \\ - \left(\gamma(t-1-x) - \gamma(t-x) \right).$$

$$MI_{AP}(t, x) = -\beta(x) - \left(\kappa(t) - \kappa(t-1) \right)$$

$$MI_C(t, x) = \left(\gamma(t-1-x) - \gamma(t-x) \right)$$



Future improvement rates after time T :

$$MI(T + t, x) = MI_{AP}(T + t, x) + MI_C(T + t, x)$$

for $t = 1, 2, \dots$

Initial improvements \longrightarrow long term rates:

$$MI_{AP}(T + t, x) \rightarrow L_{AP}(x) \text{ as } t \rightarrow \infty$$

$$MI_C(T + t, x + t) \rightarrow L_C(T - x) \text{ as } t \rightarrow \infty$$



CMI mortality improvements

- Age-period convergence period: τ_{AP} (Default ≤ 20)
- Cohort convergence period: τ_C (Default ≤ 40)
- Define $u_{AP} = \min\{t/\tau_{AP}, 1\}$ and $u_C = \min\{t/\tau_C, 1\}$
- Then

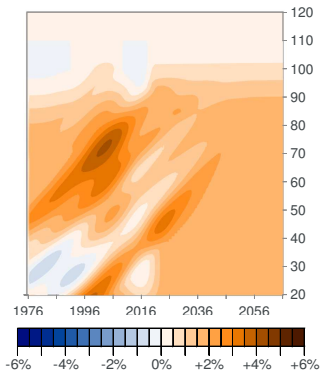
$$MI_{AP}(T + t, x) = L_{AP}(x) + (MI_{AP}(T, x) - L_{AP}(x)) (1 - 3u_{AP}^2 + 2u_{AP}^3)$$

$$MI_C(T + t, x + t) = L_C(T - x) + (MI_C(T, x) - L_C(T - x)) (1 - 3u_C^2 + 2u_C^3)$$

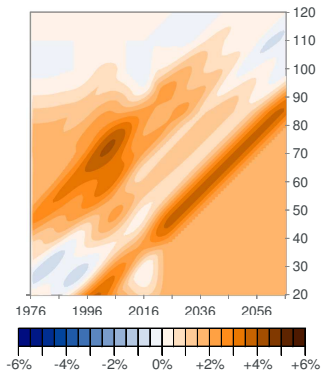
CMI: default vs persistent cohort effect ($\tau_C = 1000$)

Projected mortality improvements: EW Males

Standard cohort convergence to zero



Persistent cohort effects



(Source: outputs from CMI_2016 v01 2017-03-27.xlsm)

- Version 1:

- Use CMI to generate central $\hat{m}(T + t, x)$
- Use [CBD-X] to generate sample paths *relative to* $\hat{m}(T + t, x)$ ($k = 1, \dots, 10000$)

$$m^{(k)}(T + t, x) = \frac{m_{CBD}^{(k)}(T + t, x)}{\bar{m}_{CBD}(T + t, x)} \hat{m}(T + t, x)$$

- Version 2 (many forms):

- Use CMI to generate central $\hat{m}(T + t, x) \rightarrow \hat{a}(T, x)$
- Use [CBD-X] to generate sample PV's *relative to* $\hat{a}(T + t, x)$ ($k = 1, \dots, 10000$)

$$a^{(k)}(T, x) = \frac{a_{CBD}^{(k)}(T, x)}{\bar{a}_{CBD}(T, x)} \hat{a}(T, x)$$

Standard Random-Walk Model:

$$\kappa_k(T+t) = \kappa_k(T+t-1) + \mu_k + \epsilon_k(t)$$

Future improvement rates

$$MI(T+t, x) = MI_{AP}(T+t, x) + MI_C(T+t, x)$$

for $t = 1, 2, \dots$

$$MI_{AP}(T+t, x) = -\beta_1(x)\mu_1 - \beta_2(x)\mu_2 - \beta_3(x)\mu_3$$

$$\begin{aligned} MI_C(T+t, x+t) &= MI_C(T, x) \\ &= \gamma(T-1-x) - \gamma(T-x) \end{aligned}$$

New: Random-Walk Model with Time-Dependent Drift

$$\kappa_k(T+t) = \kappa_k(T+t-1) + \mu_k(t) + \epsilon_k(t)$$

Future improvement rates

$$MI(T+t, x) = MI_{AP}(T+t, x) + MI_C(T+t, x)$$

for $t = 1, 2, \dots$

$$MI_{AP}(T+t, x) = -\beta_1(x)\mu_1(t) - \beta_2(x)\mu_2(t) - \beta_3(x)\mu_3(t)$$

$$MI_C(T+t, x+t) = MI_C(T, x)$$



Potential choices for $\mu_k(t)$

Version 1

$$\mu_k(t) = \mu_k(\infty) + (\mu_k(0) - \mu_k(\infty))\phi^t$$

$$\tau = -\ln 2 / \ln \phi = \text{half life}$$

Version 2

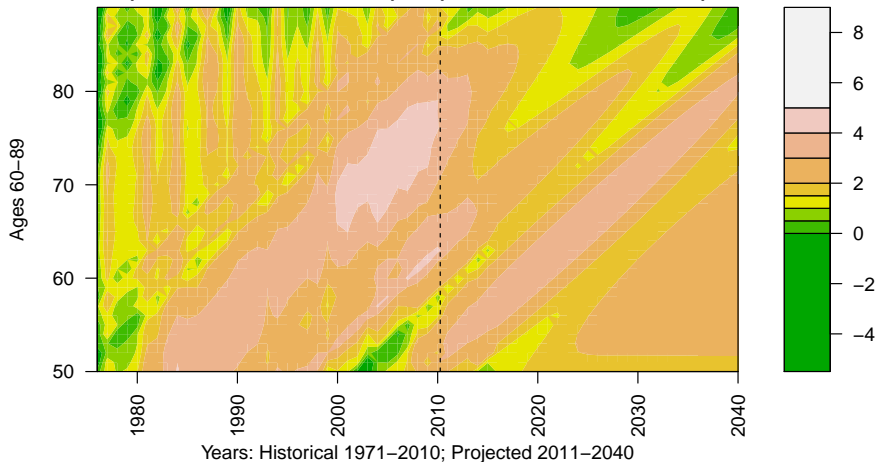
$$\mu_k(t) = \mu_k(\infty) + (\mu_k(0) - \mu_k(\infty))(1 - 3u_{AP}^2 + 2u_{AP}^3)$$

$$u_{AP} = \min\{t/\tau_{AP}, 1\} \quad (\text{similar to CMI}).$$

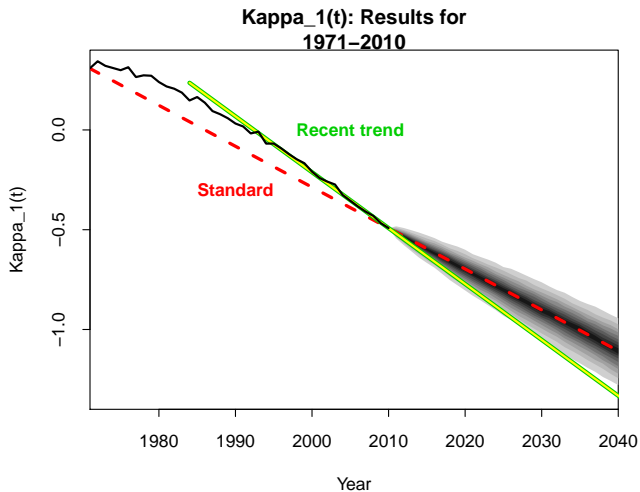


CBD-X: 1971-2010 + Standard Central Forecast

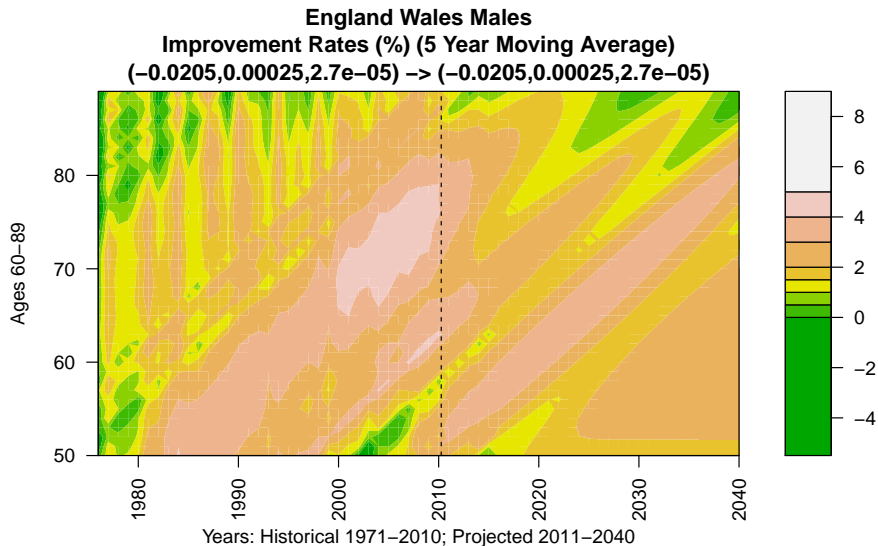
England Wales Males
Improvement Rates (%) (5 Year Moving Average)
(-0.0205,0.00025,2.7e-05) → (-0.0205,0.00025,2.7e-05)



CBD-X: 1971-2010: Standard Stochastic Forecast, $\kappa_1(t)$

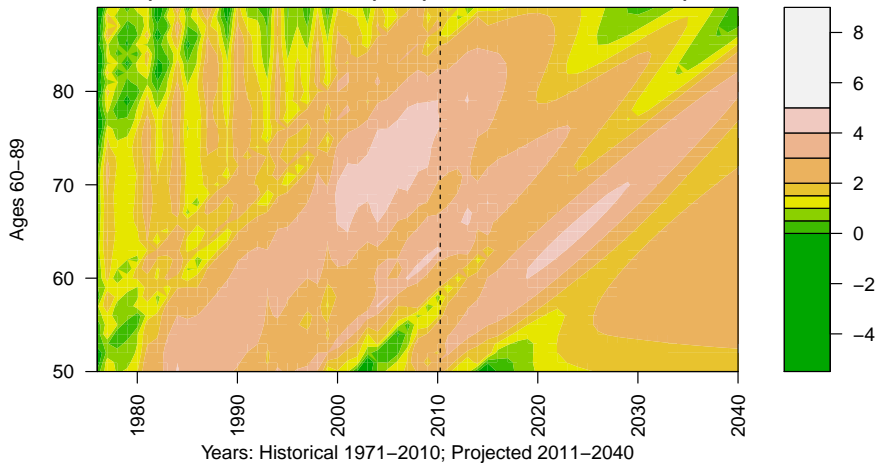


Central Improvement Rates Again



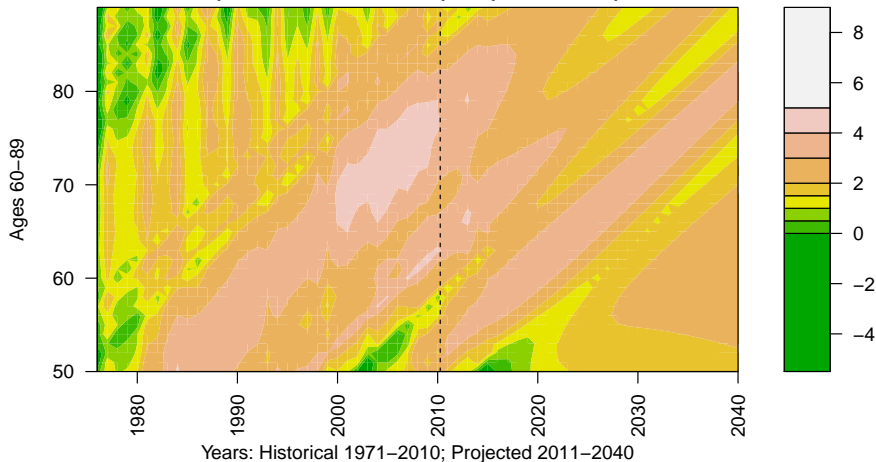
CBD-X: Time Dependent, Same Long Rates

England Wales Males
Improvement Rates (%) (5 Year Moving Average)
(-0.028,-3e-04,7e-05) \rightarrow (-0.0205,0.00025,2.7e-05)

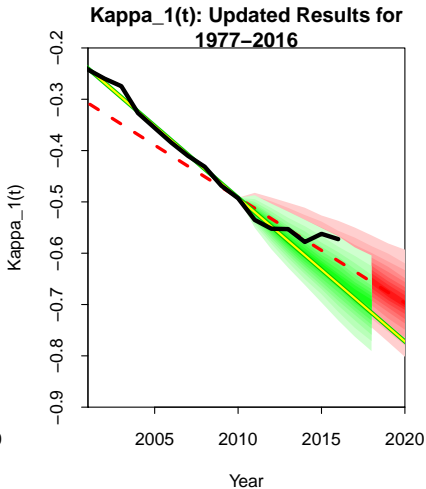
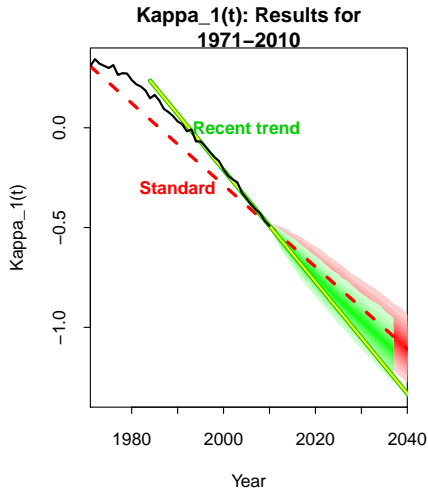


CBD-X: Time Dependent, Flat Long Rates

England Wales Males
Improvement Rates (%) (5 Year Moving Average)
(-0.028, -3e-04, 7e-05) \rightarrow (-0.0205, 0, 0)



$\kappa_1(t)$: Standard vs Time-Dependent Forecast 1971-2010 vs 1977-2016 outcome



- Exact CBD-X/CMI match requires:
 - CMI $\beta(x)$ quadratic in x
 - CMI long term improvement rate quadratic
(data do not support flat long term improvement rate)
(lower rate at high ages \Rightarrow financial consequences)
 - Same age-period transition to long rate
 - CMI cohort convergence period $\tau_C = \infty$
- Default CMI: flat long-term AP mortality improvements
 \Rightarrow requires CBD-X

$$\mu_2(\infty) = \mu_3(\infty) = 0$$

and $\mu_1(\infty) =$ CMI long-term AP improvement rate



Consistency with the full stochastic model

- Alternatives to the random walk model:
 - Börger et al. (2013, ASTIN B.)
 - Liu and Li (2017, ASTIN B.)
 - Both attempt to capture local trend changes
 - Mavros et al. (2017, NAAJ)
- Both \Rightarrow random walk around a stochastic drift, $\mu_k(t)$
 \Rightarrow central forecast $\hat{\mu}(t)$
- Potential adjustments to both models (???)
 $\Rightarrow \hat{\mu}(t) = \mu(\infty) + \phi^t(\mu(0) - \mu(\infty))$
- Alternative approach: Richards et al. (2018, IFoA)
Stochastic version of CMI APCI model
ARIMA model for $\kappa(t) \Rightarrow$ time dependent $\hat{\mu}(t)$



Summary

- Work in progress!
- Framework here: $CBD - X \longrightarrow$ other models
- Historical data: alternative sub-staged approach
- Central forecasts: adapt [CBD-X] to mimic CMI
- Common ground exists between [CBD-X] and *actively managed* CMI

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Thank You!

Questions?

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W2: www.macs.hw.ac.uk/~andrewc/ARResources



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