

The International Actuarial Association



MODELS FOR STOCHASTIC MORTALITY

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and

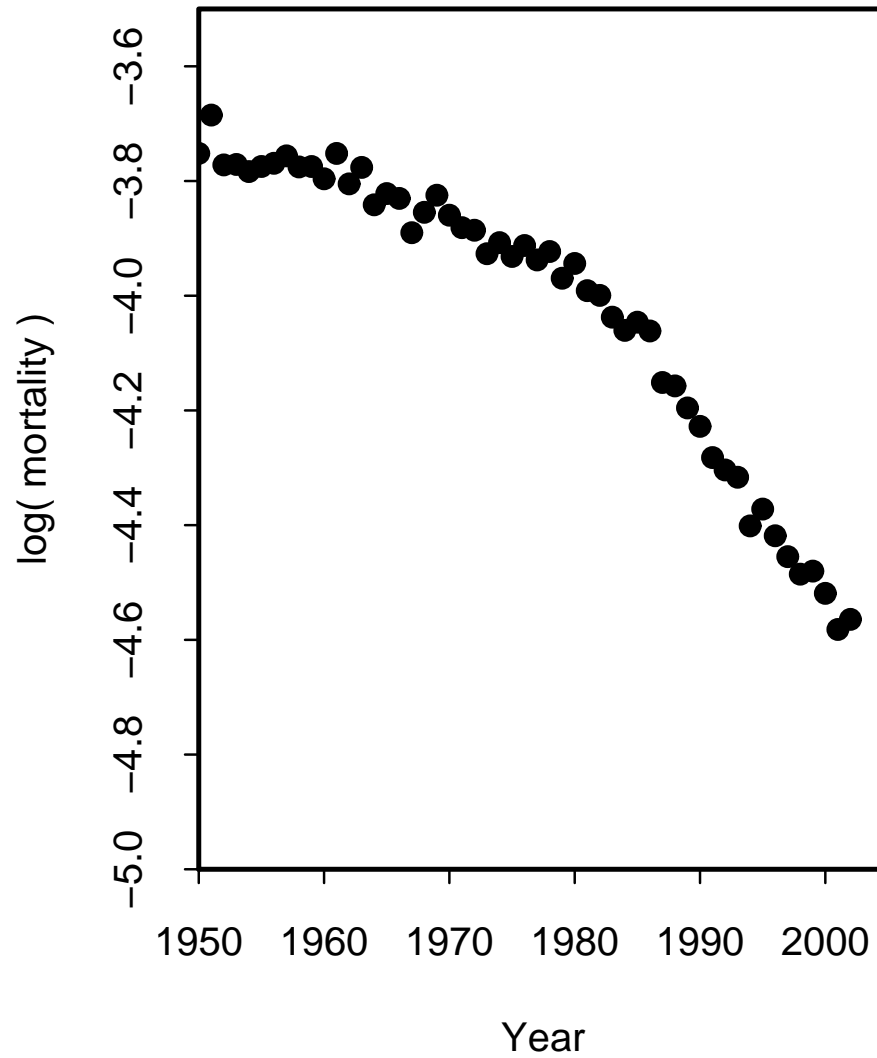
The Maxwell Institute, Edinburgh

Plan

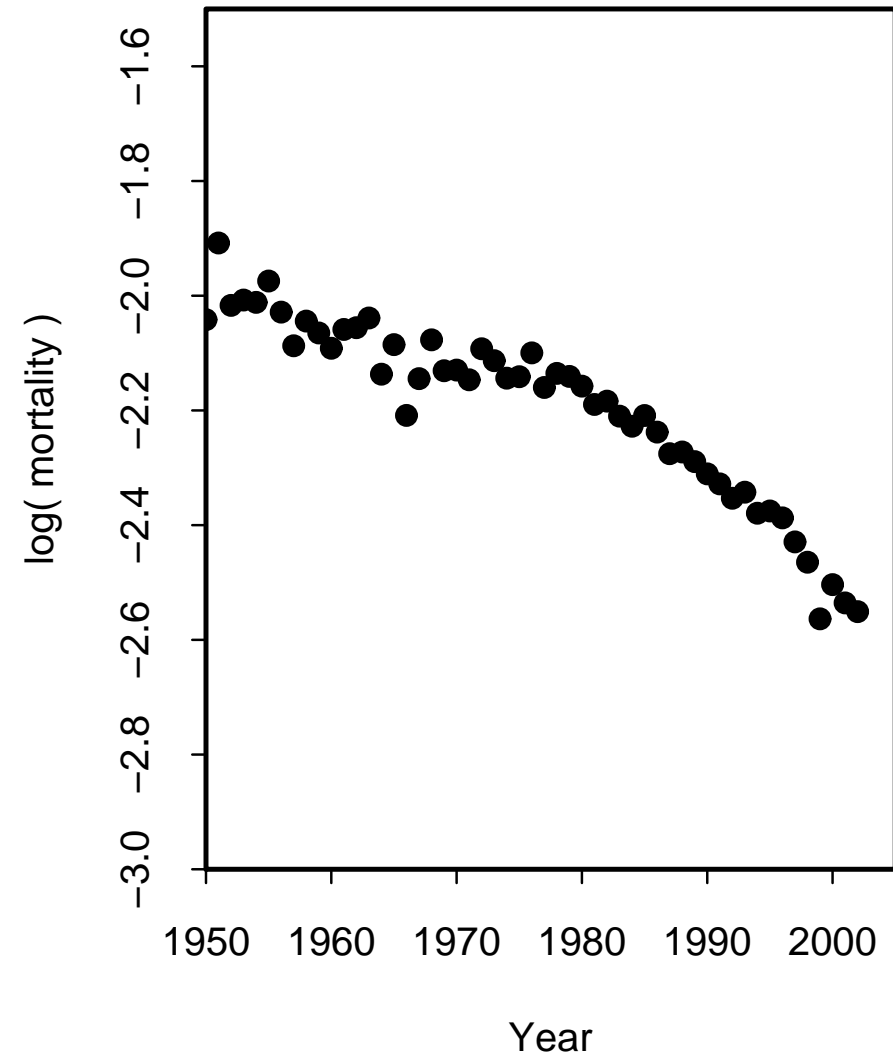
- Introduction + data
- A simple model for stochastic mortality
 - Parameter uncertainty
- Comparing different models
 - Model risk
 - Model selection criteria

England and Wales log mortality rates 1950-2002

Age 60



Age 80



The facts about mortality:

- Mortality rates are falling
- Systematic randomness from year to year
- Uncertain improvement rate
- Different ages \Rightarrow Different improvement rates

Stochastic Models for Future Mortality

Limited historical data \Rightarrow

- No single model is 'the right one'

limited data \Rightarrow **Model risk**

- Even with the right model

limited data \Rightarrow **Parameter risk**

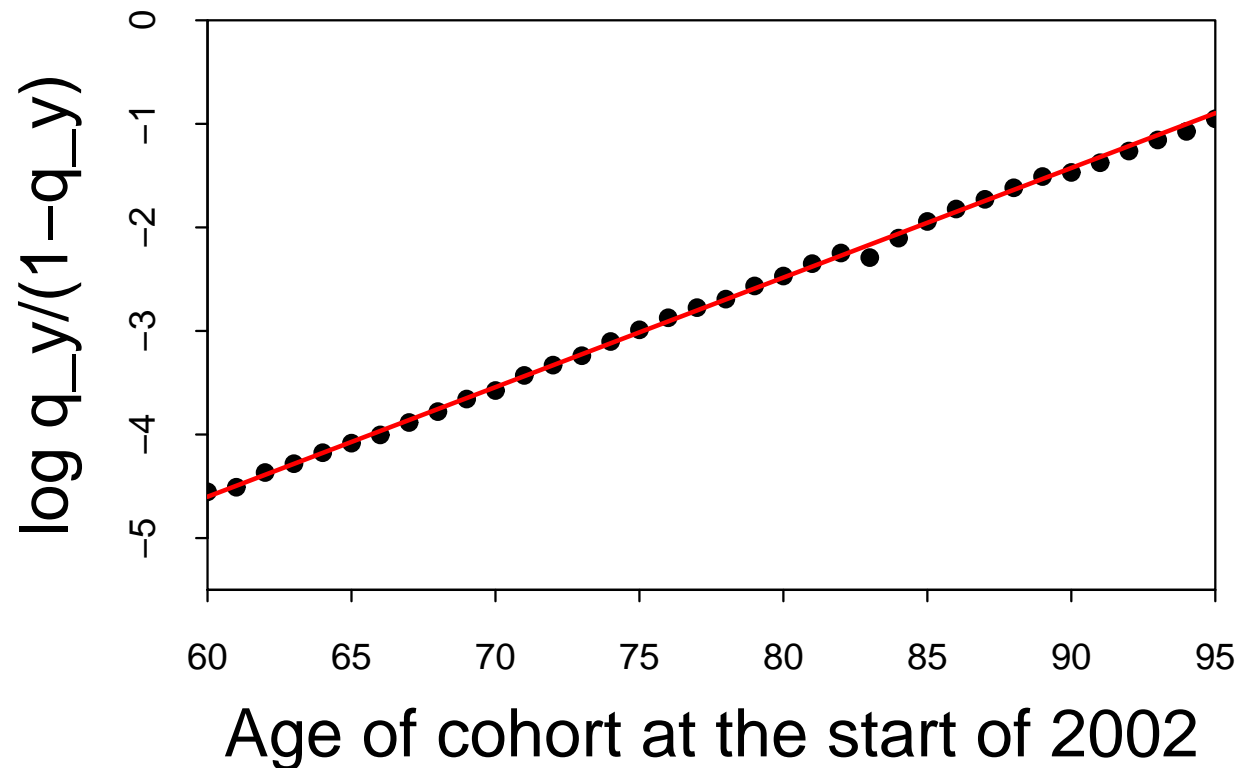
Why is it important to model stochastic mortality?

- Good risk management

[Process risk, parameter uncertainty, model risk]

- Calculating *quantile* reserves
- Valuing and hedging complex life insurance contracts with guarantees

Case study: England and Wales males, age 60-90



q_y = mortality rate at age y in 2002

Data suggests $\log q_y/(1 - q_y)$ is linear

A TWO-FACTOR PARAMETRIC TIME-SERIES MODEL

x = age at time t

Mortality rates for the year t to $t + 1$:

$$\text{logit } q(t, x) = \kappa_1(t) + \kappa_2(t) (x - \bar{x})$$

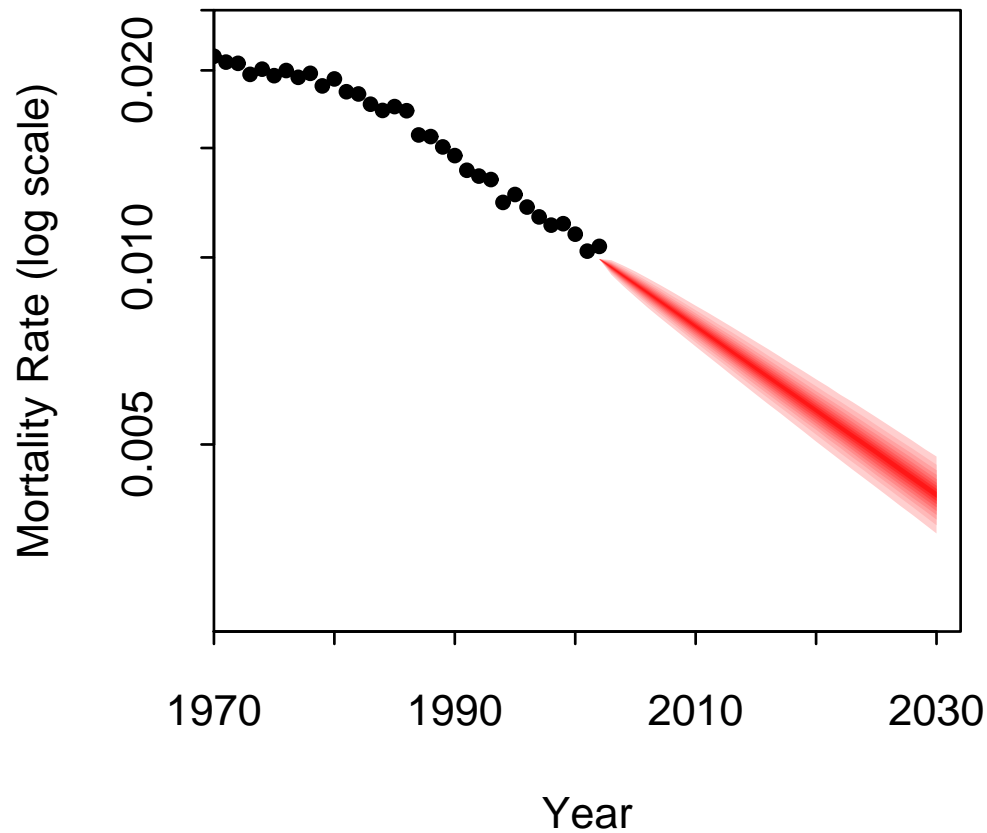
We model $\kappa(t) = (\kappa_1(t), \kappa_2(t))'$ as a random-walk

$$\kappa(t + 1) = \kappa(t) + \mu + CZ(t + 1)$$

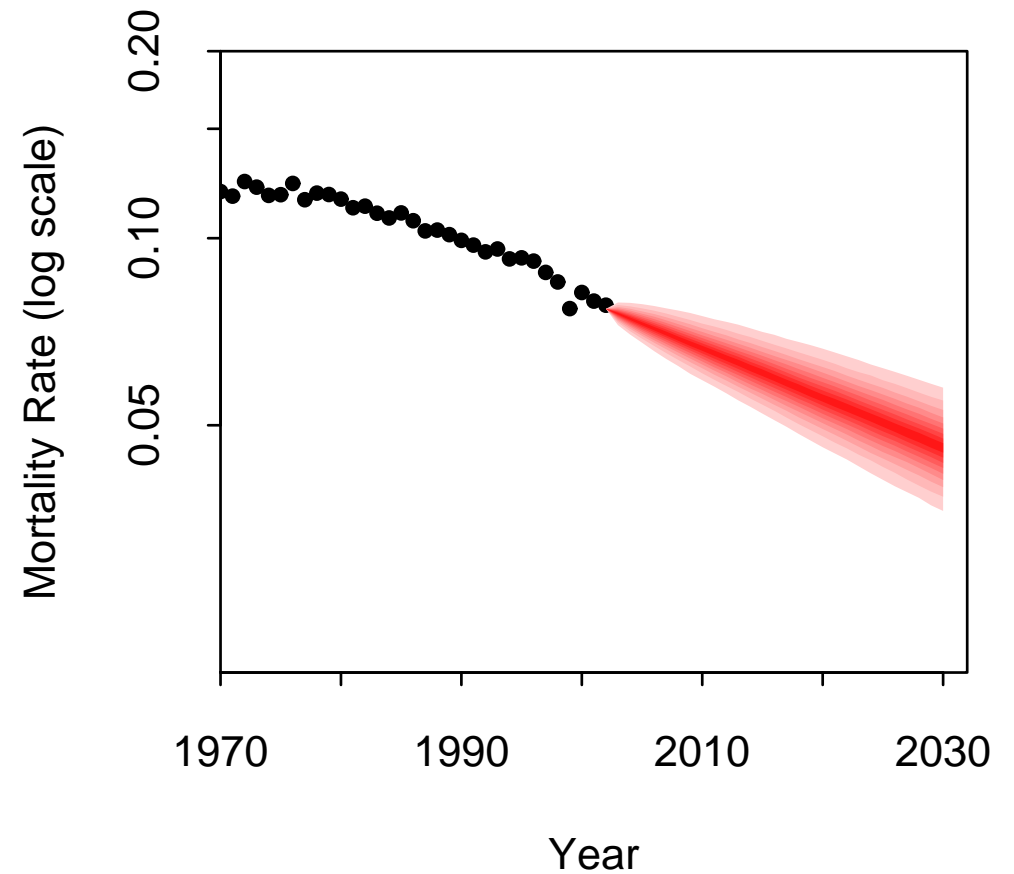
- Estimate μ and $V = CC'$
- Quantify parameter uncertainty in μ and V

Simulated mortality rates: 90% confidence intervals without parameter uncertainty

Age 60

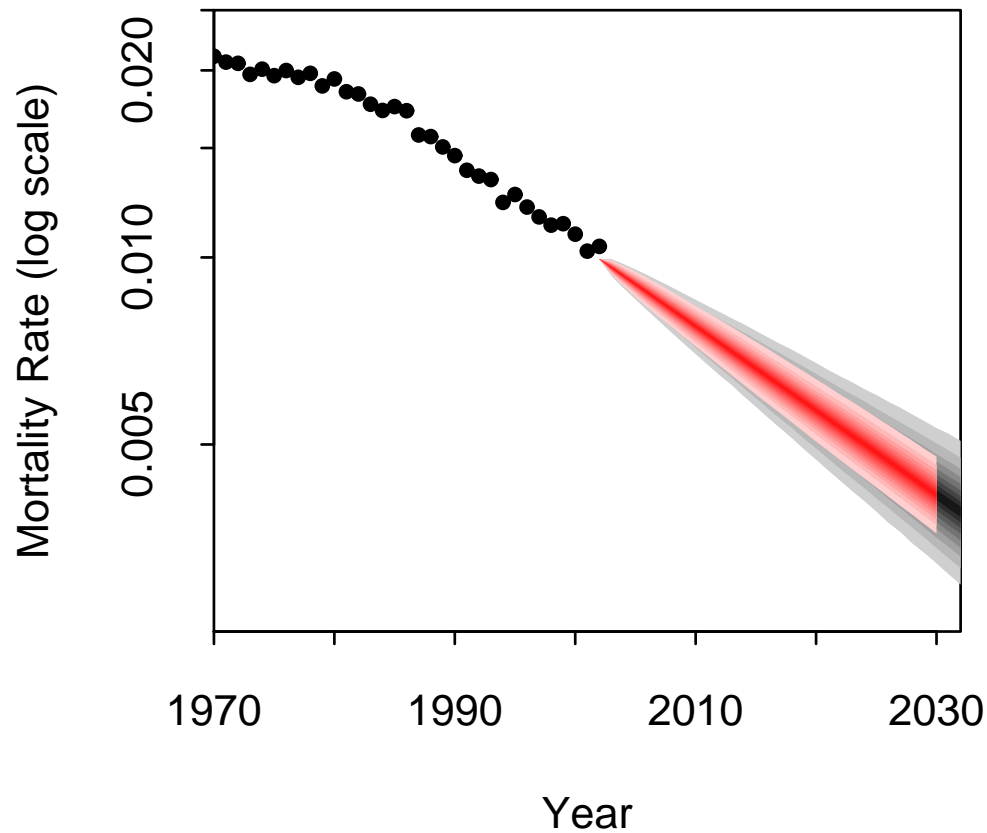


Age 80

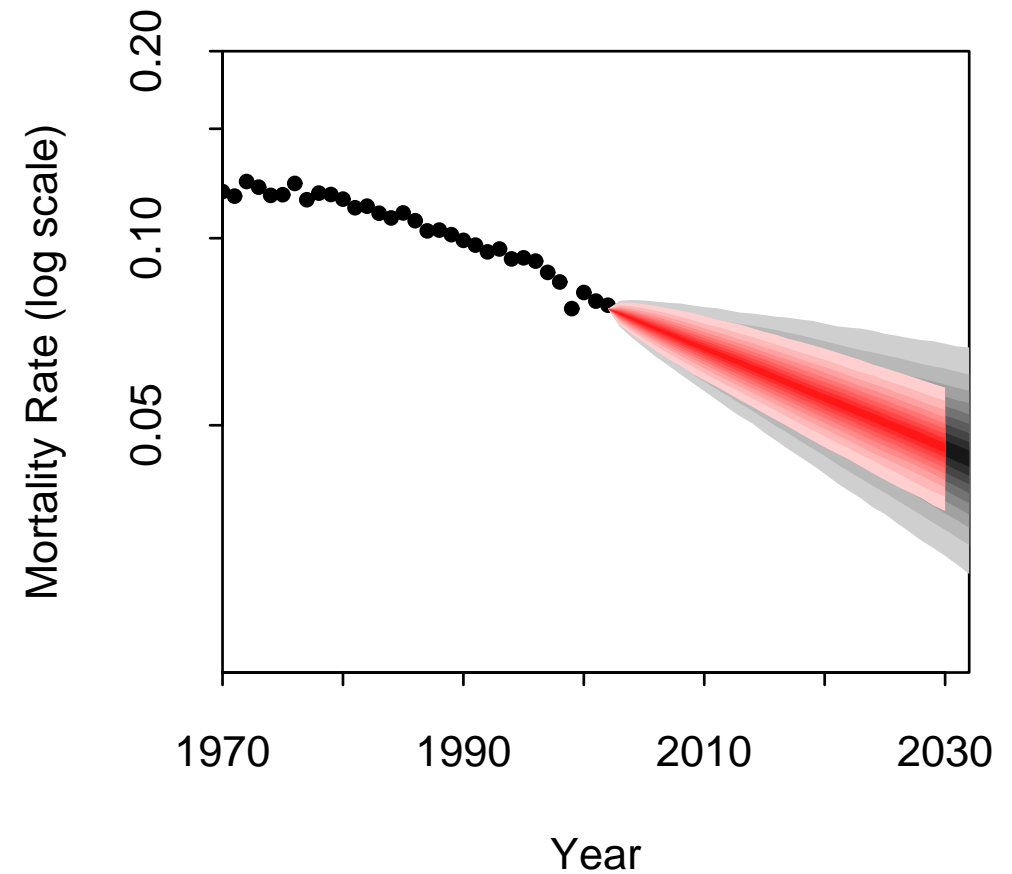


Simulated mortality rates: 90% confidence intervals with and **without** parameter uncertainty

Age 60



Age 80



Other models

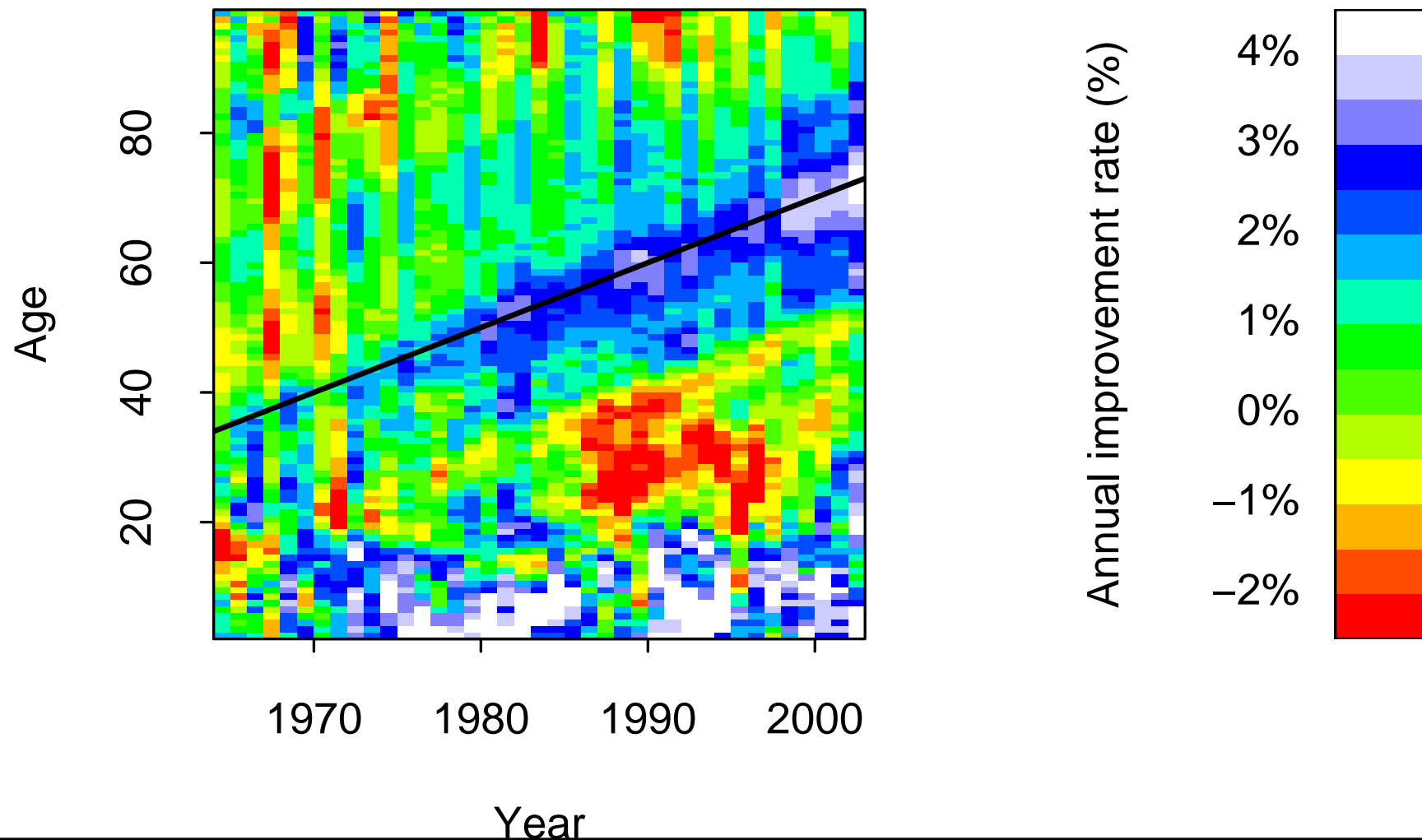
General family:

$$\text{logit } q(t, x) = \sum_{i=1}^N \beta_x^{(i)} \kappa_t^{(i)} \gamma_{t-x}^{(i)}$$

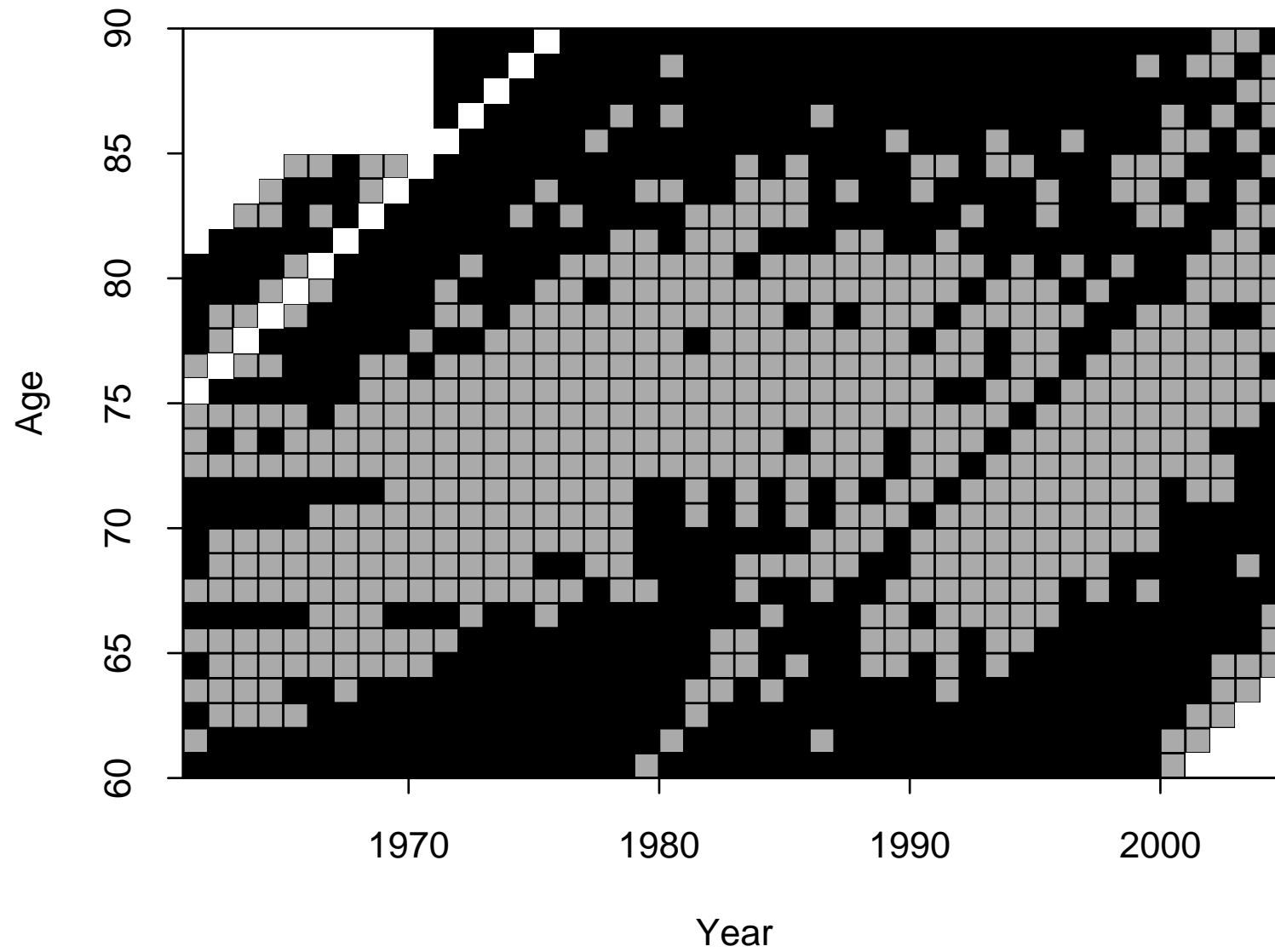
- $\beta_x^{(i)}$ = age effects
- $\kappa_t^{(i)}$ = period effects
- $\gamma_{t-x}^{(i)}$ = cohort effects
- N = number of components

Cohort Effects (e.g. Willetts, 2004)

Annual mortality improvement rates (Engl. & Wales, males)



2-factor Model: Standardised Residuals



Eight models compared (5 here; England & Wales data)

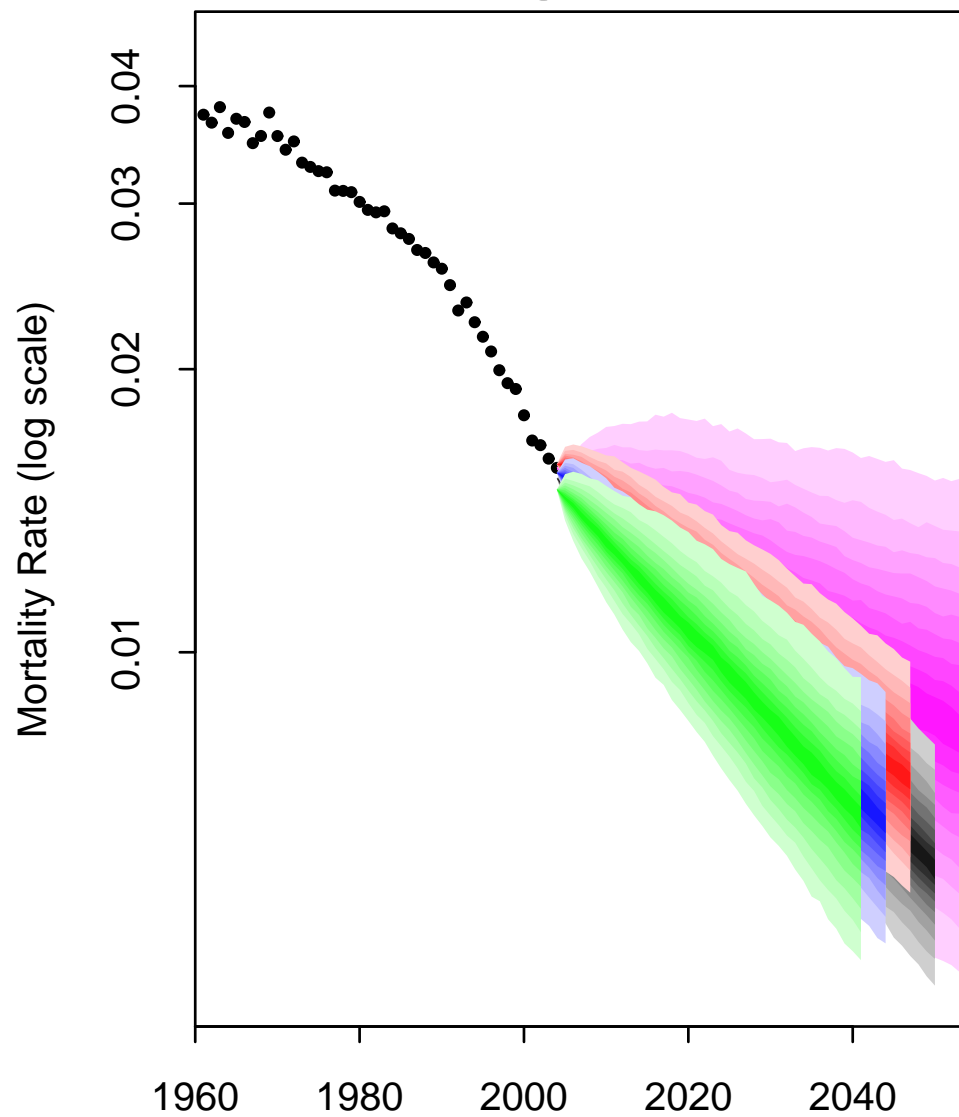
Model	Maximum log-likelihood (*)	Effective number of parameters	BIC (rank)
M1 (Lee-Carter)	-8912.7	102	-9275.8 (6)
M2 (Renshaw-Haberman)	-7735.6	203	-8458.1 (3)
M5 (Cairns-Blake-Dowd)	-10035.5	88	-10348.8 (8)
M7 (new)	-7702.1	202	-8421.1 (2)
M8 (new)	-7823.7	161	-8396.8 (1)

(*) Poisson model for deaths; E & W males, ages 60-89

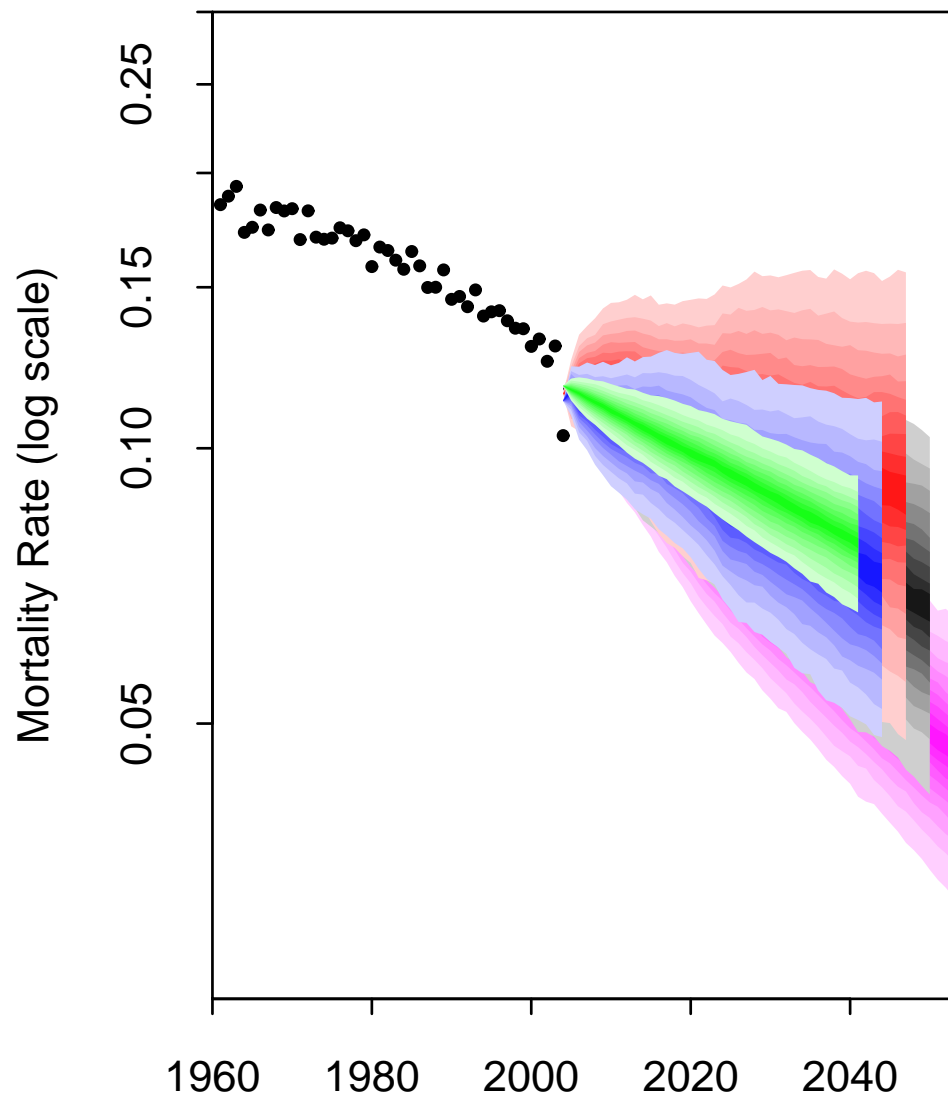
US data: top three ranks are reversed

Model risk is important

Age 65



Age 85



Model evaluation criteria

- Quality of fit (BIC)
- Robustness of parameter estimates
- Plausibility of forecasts
- Biological reasonableness
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Robustness of parameter estimates and forecasts

- Fit model to 1961-2004

Forecasts based on 1961-2004 parameter estimates

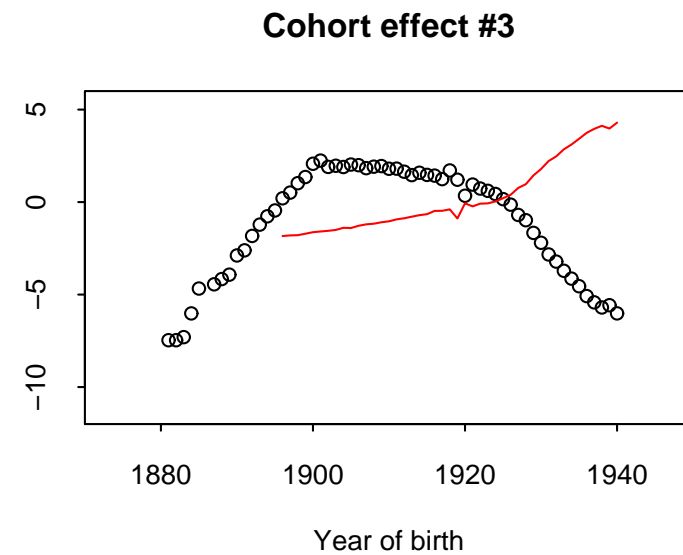
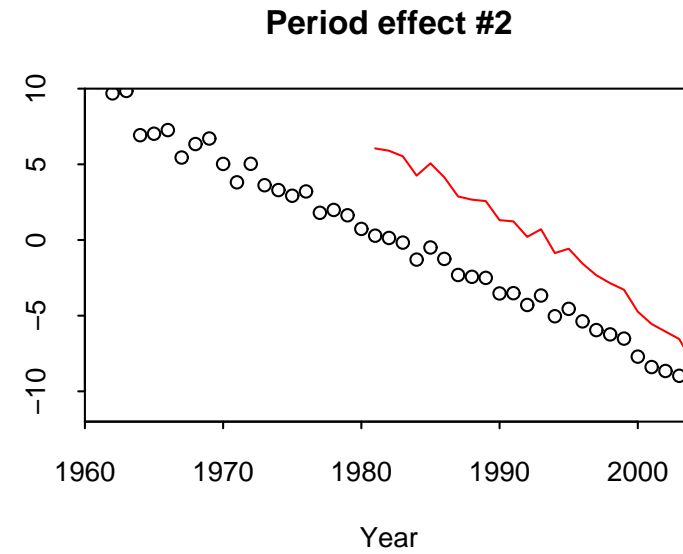
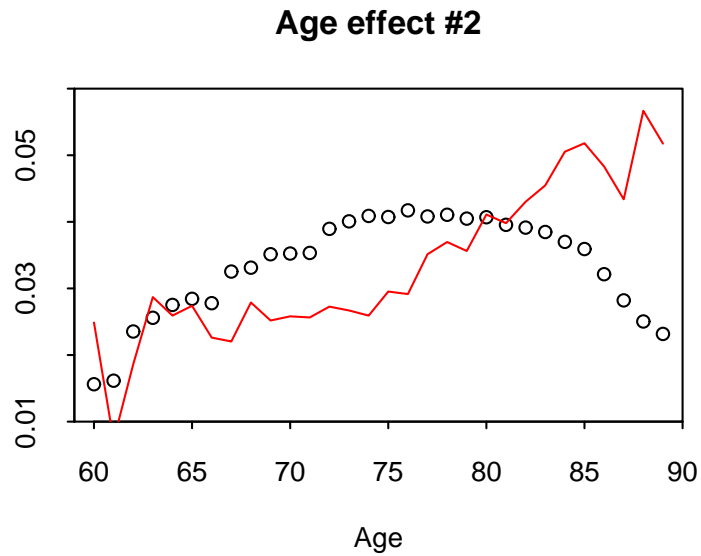
- Fit model to 1981-2004

Forecasts based on 1981-2004 parameter estimates

- Fit model to 1961-2004

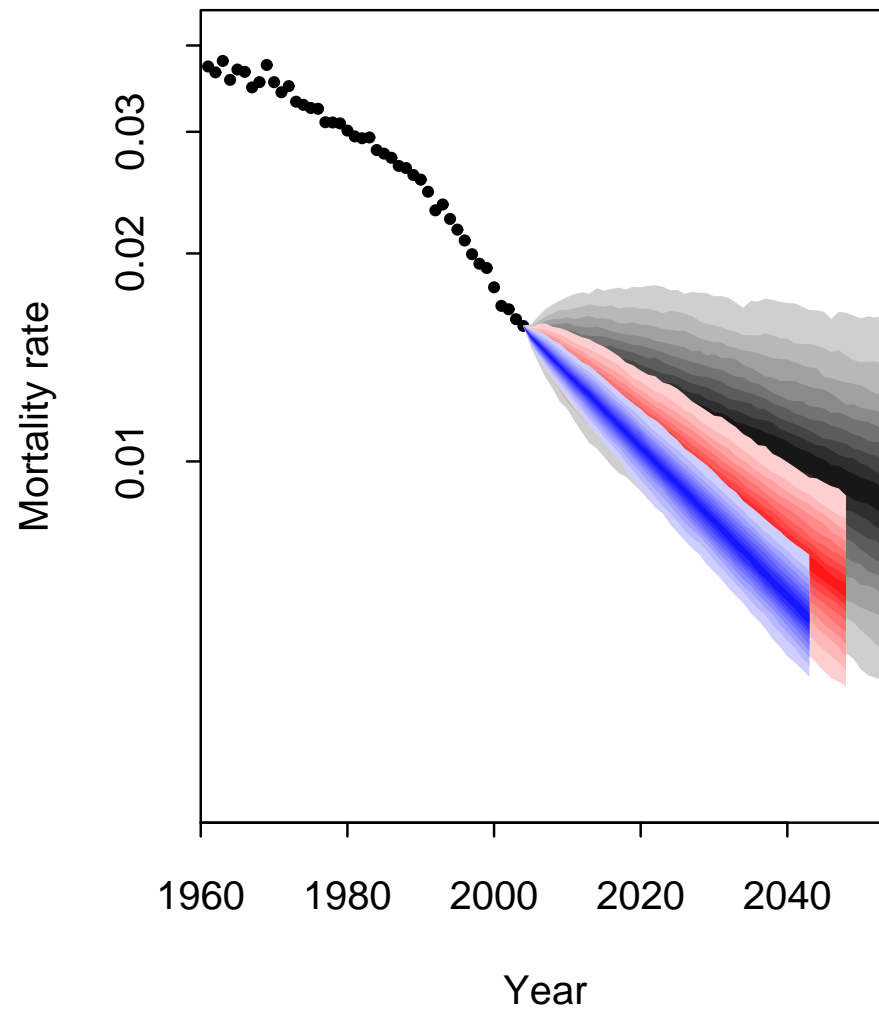
Forecasts based on 1981-2004 parameter estimates

Model M2 parameter estimates not robust

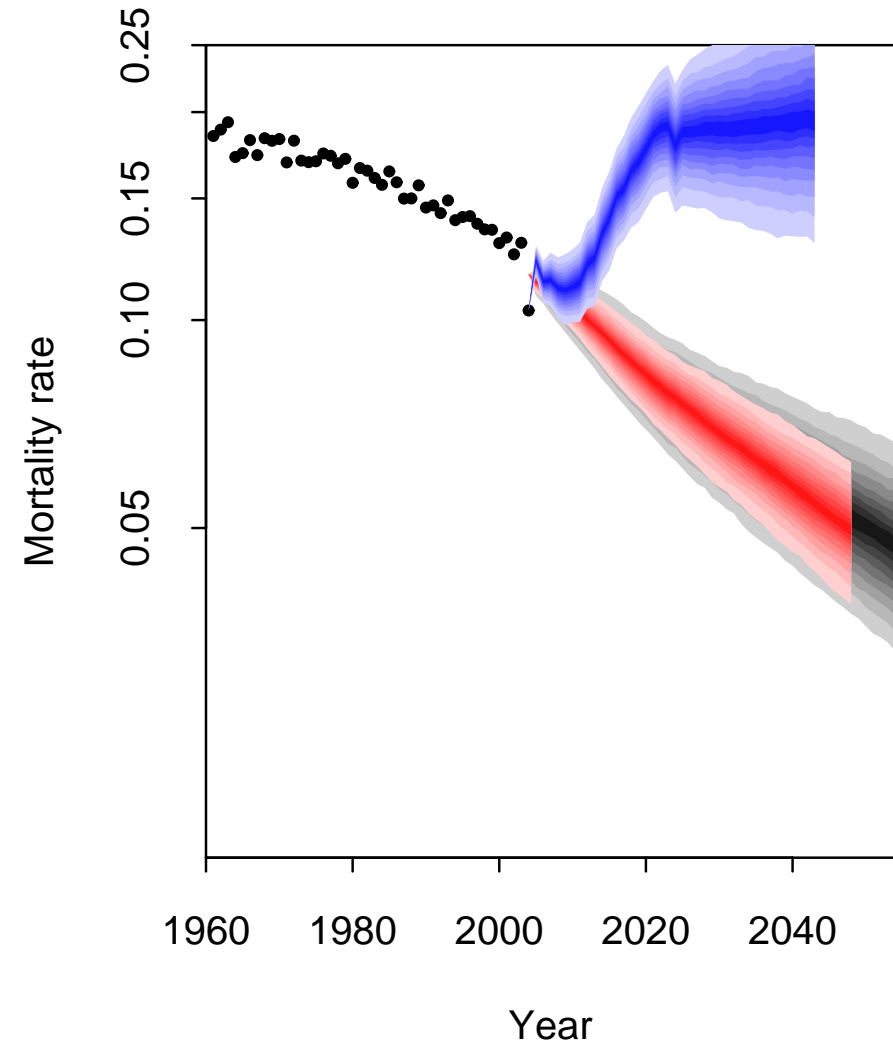


Model M2 forecasts not robust

Age 65 Mortality Rates

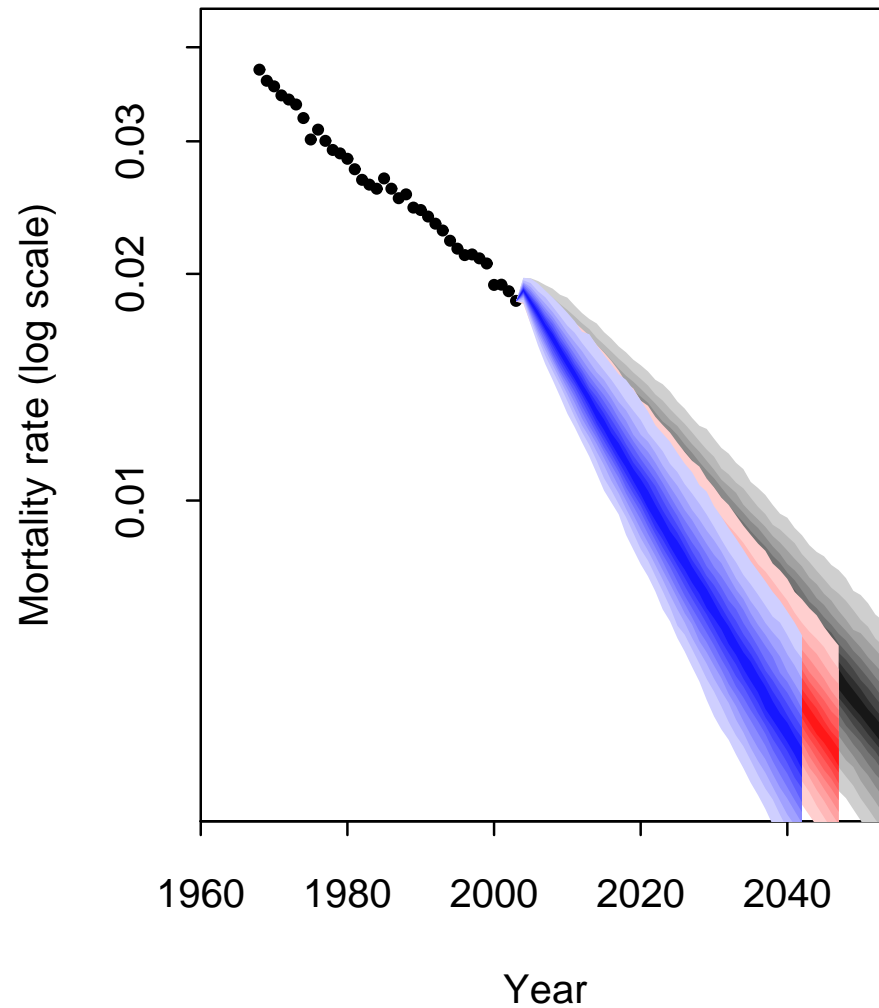


Age 85 Mortality Rates

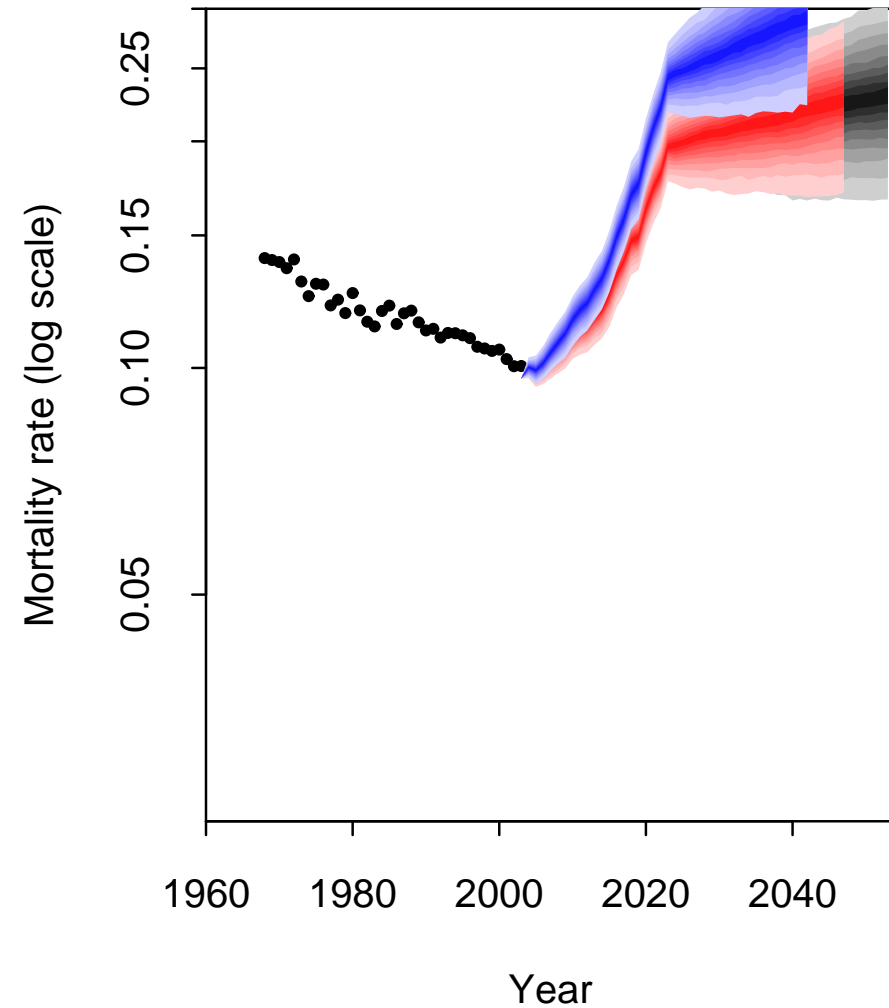


Model M8 US males forecasts are *not plausible*

Age 65 Mortality Rates (log scale)



Age 84 Mortality Rates (log scale)



Possible problems with M2 and M8

- M2 only ???:
 - Likelihood has many **local maxima**
 - Lack of smoothness in age effects
- M2 and M8:
 - **Age-Cohort effects** being used to compensate for too few **Age-Period** effects

Conclusions

- Model and parameter risk is important
- Need to use several model selection criteria
 - Quantitative: e.g. BIC
 - Qualitative

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