

MODELS FOR STOCHASTIC MORTALITY WITH PARAMETER UNCERTAINTY

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Plan

- Introduction
- Approaches to modelling mortality improvements
- A two-factor model for stochastic mortality
- Application
 - The survivor index
- Adding in a cohort effect
- Conclusions

The facts about mortality:

- Life expectancy is increasing.
- Future development of life expectancy is uncertain.

“Longevity risk”

Longevity Risk = the risk that aggregate future mortality rates are lower than anticipated

Focus here: Mortality rates above age 60

STOCHASTIC MORTALITY

n lives, probability p of survival, N survivors

- Unsystematic mortality risk:

$$\Rightarrow N|p \sim \text{Binomial}(n, p)$$

$$\Rightarrow \text{risk is diversifiable, } N/n \longrightarrow p \quad \text{as } n \longrightarrow \infty$$

- Systematic mortality risk:

$$\Rightarrow p \text{ is uncertain}$$

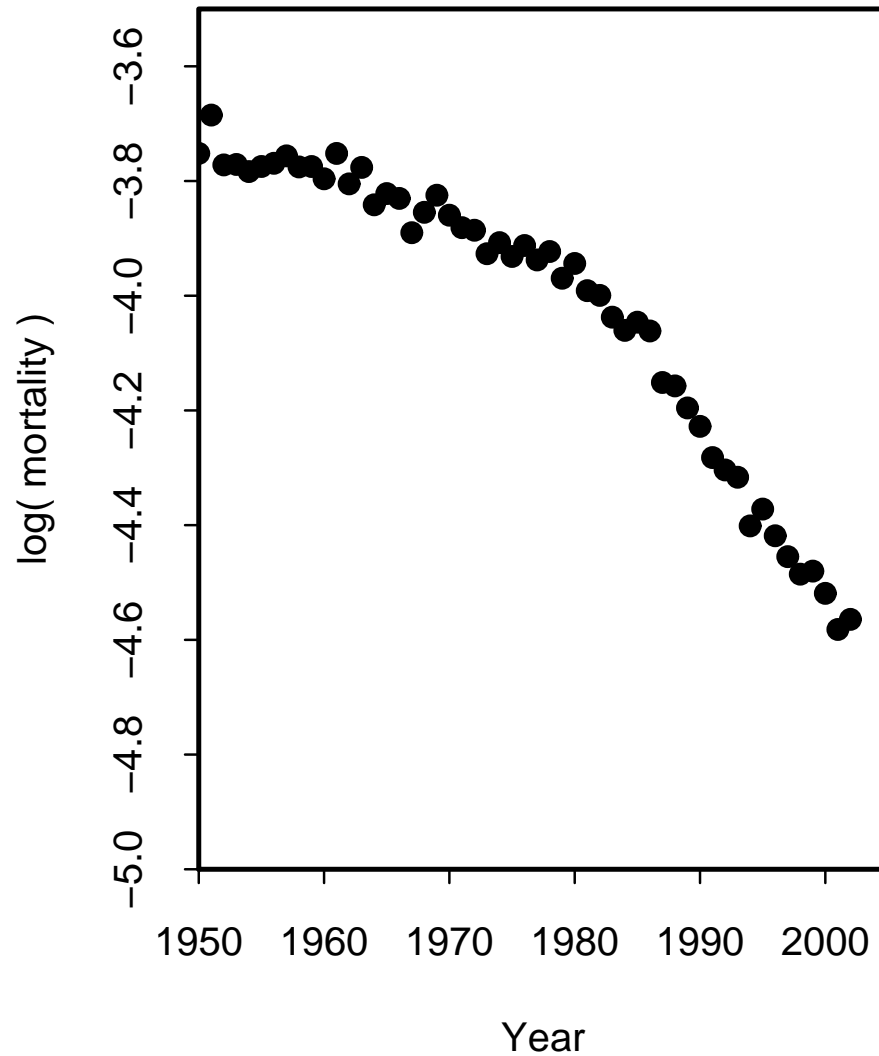
$$\Rightarrow \text{risk associated with } p \text{ is not diversifiable}$$

Where is stochastic mortality relevant?

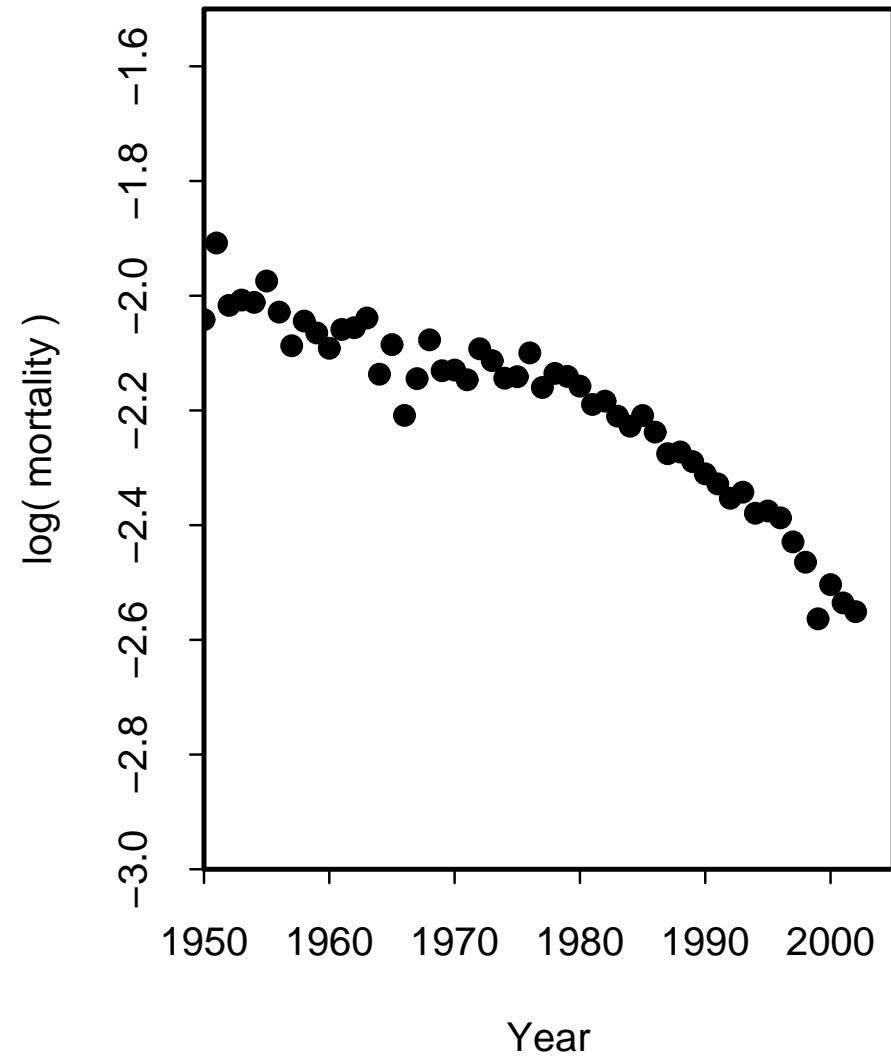
- Risk management in general
- Pension plans: what level of reserves?
- Life insurance contracts with embedded options.
- Pricing and hedging longevity-linked securities.

England and Wales log mortality rates 1950-2002

Age 60



Age 80



Stochastic Models

Different approaches to modelling

- Lee-Carter
- P-splines
- Parametric, time-series models
- Market models
- Age-Period-Cohort extensions

Stochastic Models

Limited historical data \Rightarrow

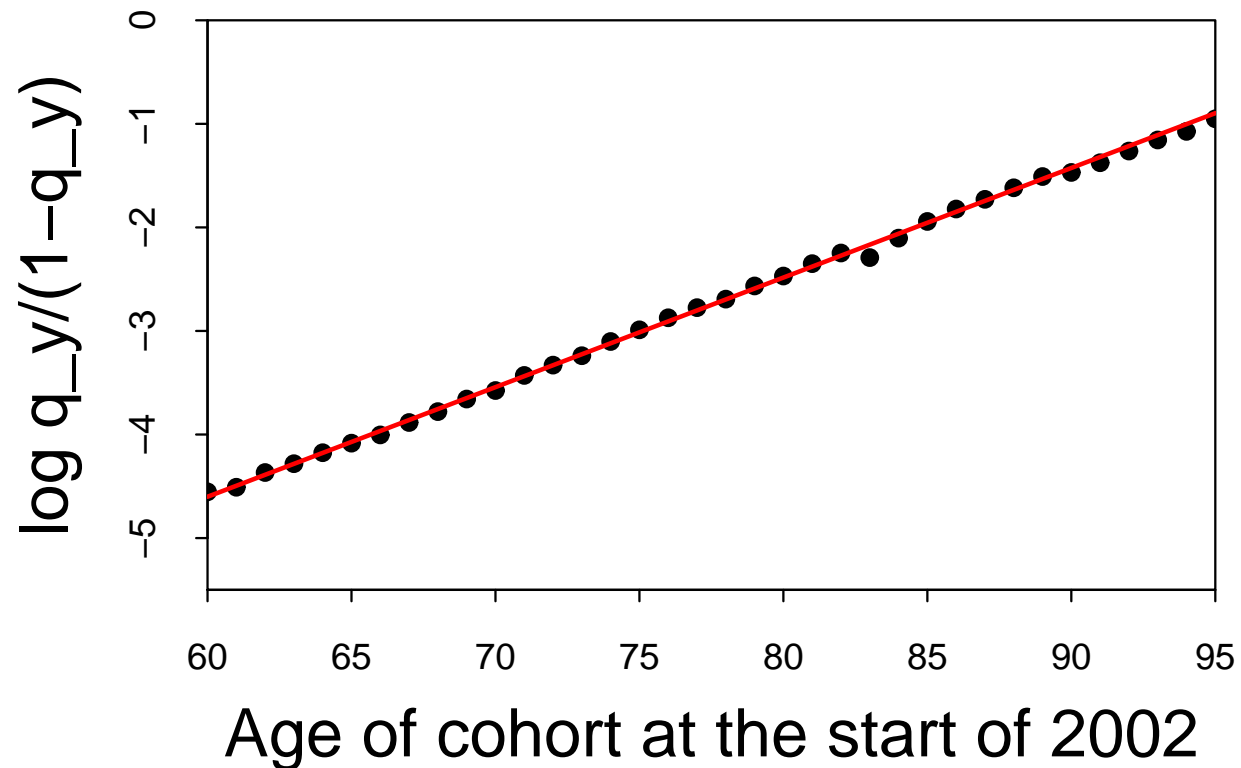
- No single model is 'the right one'

limited data \Rightarrow **Model risk**

- Even with the right model

limited data \Rightarrow **Parameter risk**

Case study: England and Wales males, age 60-95



q_y = mortality rate at age y in 2002

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

PARAMETRIC TIME-SERIES MODELS

- $x =$ age at time t
- $t - x =$ approximate year of birth
- $q(t, x)$ Mortality rates for the year t to $t + 1$ for individuals aged x at t :
- $N =$ number of factors

PARAMETRIC TIME-SERIES MODELS

General class of models

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

“Parametric” $\Rightarrow \beta_x^{(i)}$ is a simple function of x

OR

$$q(t, x) = \frac{\exp \left(\sum_{i=1}^N \beta_x^{(i)} \kappa_t^{(i)} \gamma_{t-x}^{(i)} \right)}{1 + \exp \left(\sum_{i=1}^N \beta_x^{(i)} \kappa_t^{(i)} \gamma_{t-x}^{(i)} \right)}$$

Estimation

- **Data:** Deaths $D(t, x)$, Exposures $E(t, x)$
 \Rightarrow Crude death rates $\hat{m}(t, x) = D(t, x) / E(t, x)$
- Underlying $m(t, x) = -\log[1 - q(t, x)]$
(by assumption)
- $D(t, x) \sim$ independent Poisson $\left(m(t, x) E(t, x) \right)$
- Maximum likelihood $\Rightarrow \hat{\beta}_x^{(i)}$, $\hat{K}_t^{(i)}$ and $\hat{\gamma}_{t-x}^{(i)}$

TWO PARAMETRIC TIME-SERIES MODELS

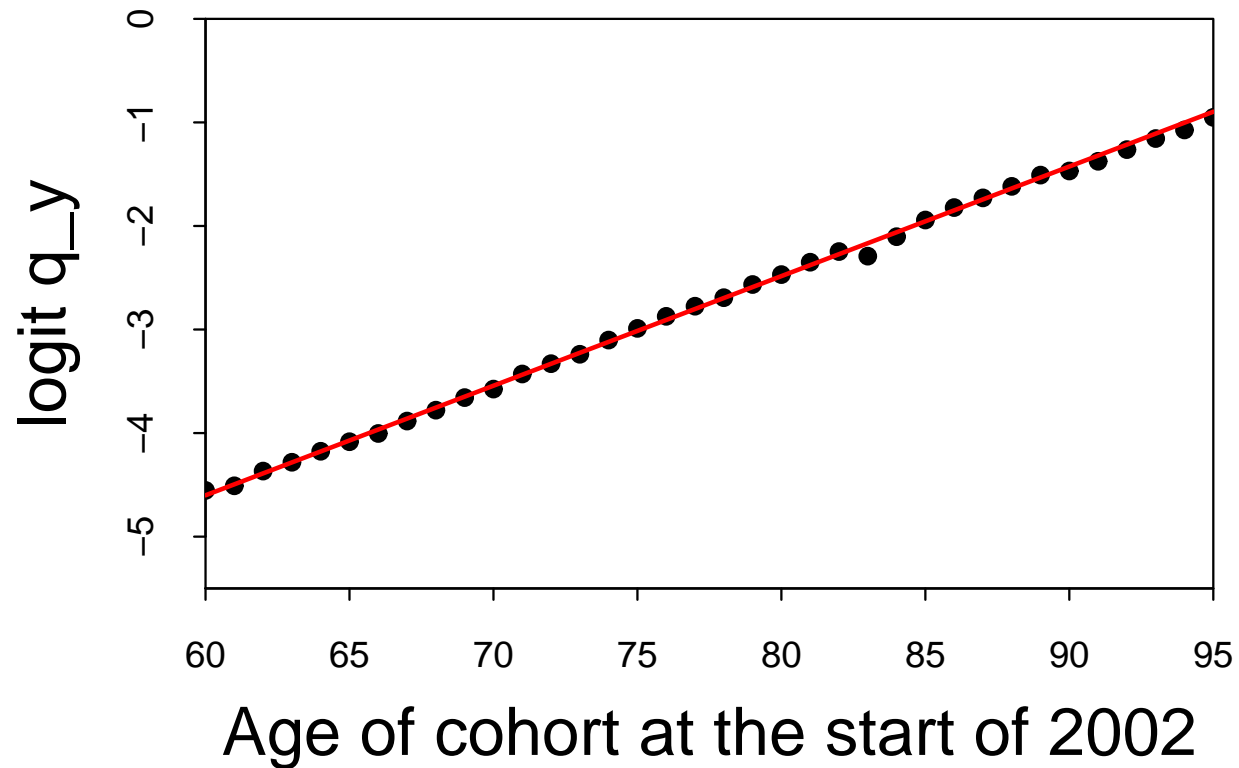
Model 1 (Age-Period model):

$$\text{logit } q(t, x) = \kappa_t^{(1)} + \kappa_t^{(2)} (x - \bar{x})$$

Model 2 (Age-Period-Cohort model):

$$\begin{aligned} \text{logit } q(t, x) = & \kappa_t^{(1)} + \kappa_t^{(2)} (x - \bar{x}) \\ & + \kappa_t^{(3)} [(x - \bar{x})^2 - \sigma_x^2] \\ & + \gamma_{t-x}^{(4)} \end{aligned}$$

Model 1: Case study – England and Wales males

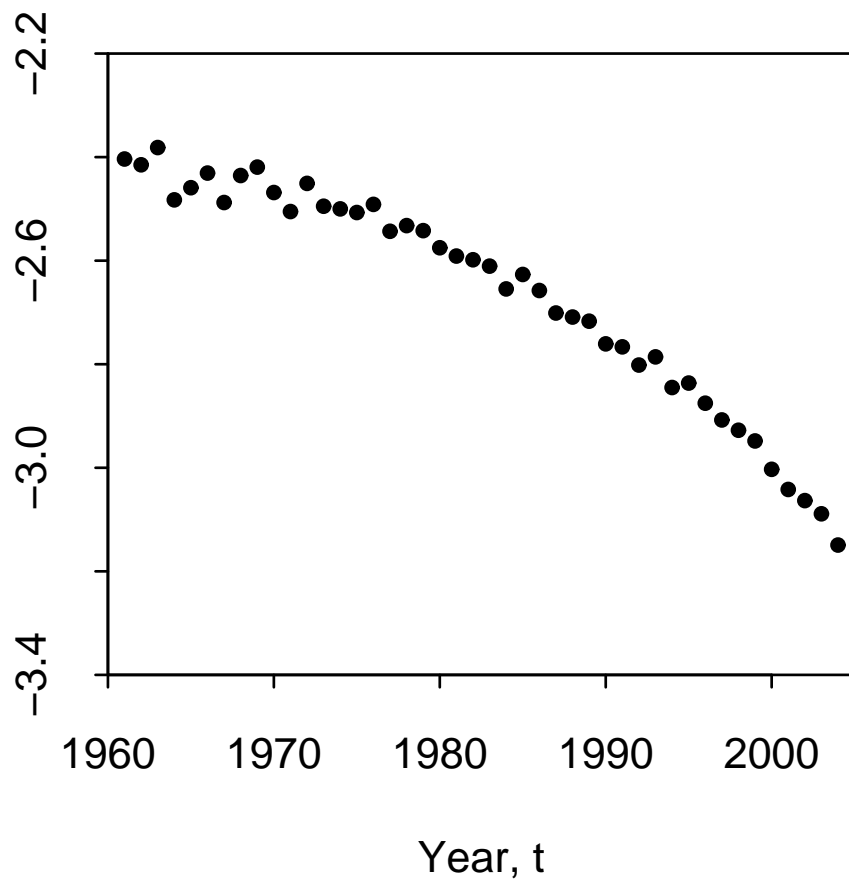


$\kappa_t^{(1)} \Rightarrow$ level

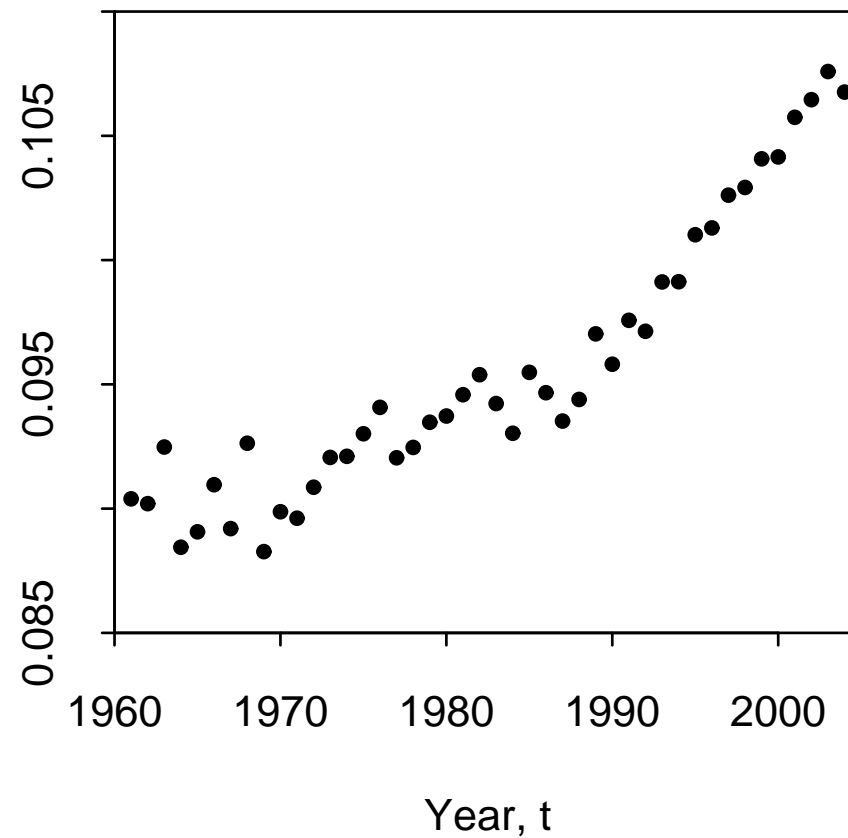
$\kappa_t^{(2)} \Rightarrow$ slope

Model 1

2-factor model: $\text{Kappa}_1(t)=1$



2-factor model: $\text{Kappa}_2(t)$



$$\kappa_t = (\kappa_t^{(1)}, \kappa_t^{(2)})'$$

Model: Random walk with drift

$$\kappa_{t+1} - \kappa_t = \mu + CZ(t+1)$$

- $\mu = (\mu_1, \mu_2)'$ = drift
- $V = CC'$ = variance-covariance matrix
- Estimate μ and V
- Quantify parameter uncertainty in μ and V

WHY 2 FACTORS? (i.e. $\kappa_t^{(1)}$ and $\kappa_t^{(2)}$)

Data suggest **changes in *underlying* mortality rates are not perfectly correlated across ages.**

1 factor (e.g. most Lee-Carter-based models)

⇒ changes over time in the $q(t, x)$ are perfectly correlated.

Bayesian approach to parameter uncertainty

- Jeffreys prior $p(\mu, V) \propto |V|^{-3/2}$.
- Data: vector $D(t) = \kappa_t - \kappa_{t-1}$ for $t = 1, \dots, n$
- MLE's: $\hat{\mu}$ and \hat{V} .
- Posterior:

$$V^{-1} | D \sim \text{Wishart}(n - 1, n^{-1} \hat{V}^{-1})$$

$$\mu | V, D \sim \text{MVN}(\hat{\mu}, n^{-1} V)$$

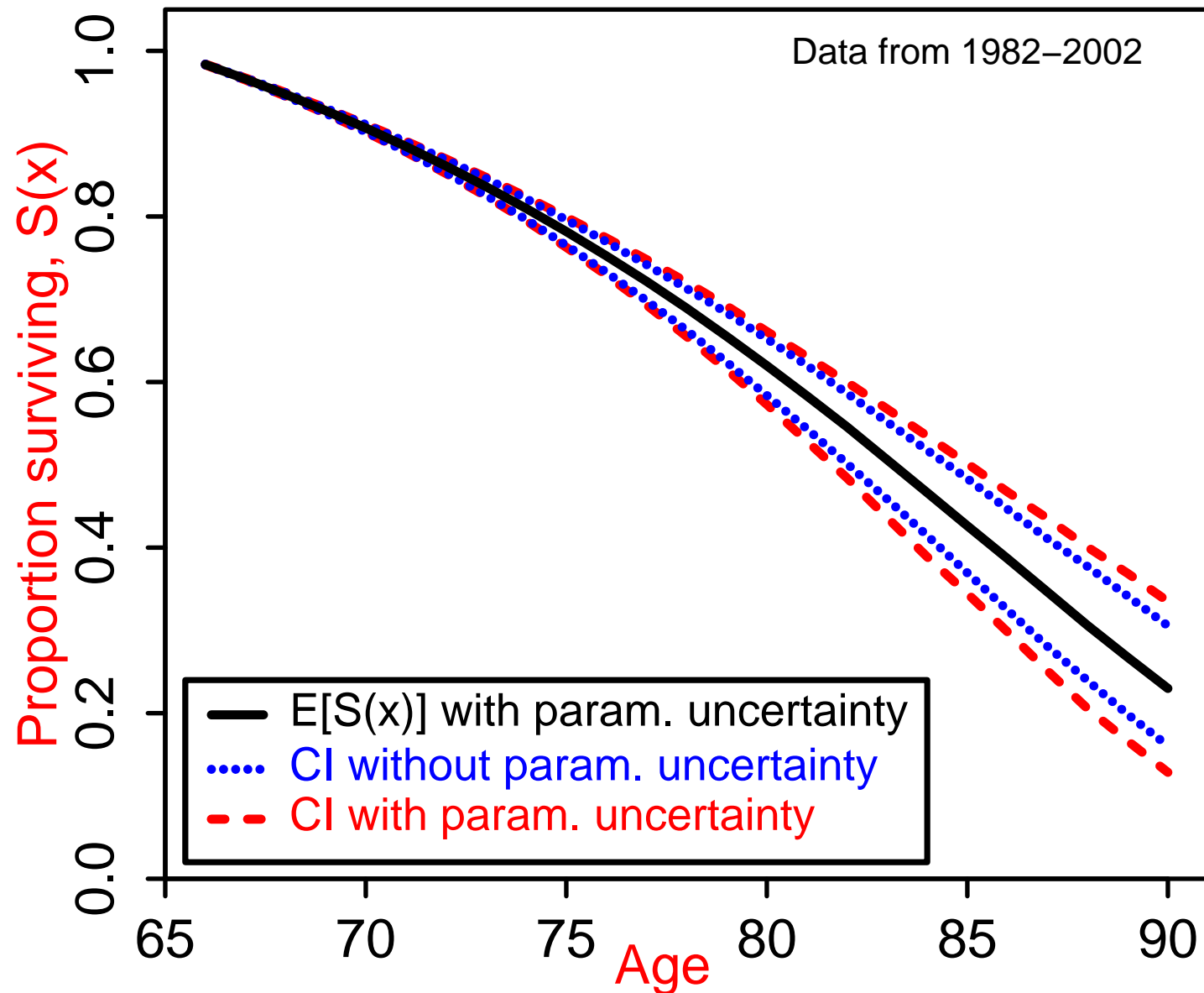
Application: cohort survivorship

- Cohort: Age x at time $t = 0$
- $S(t, x)$ = survivor index at t

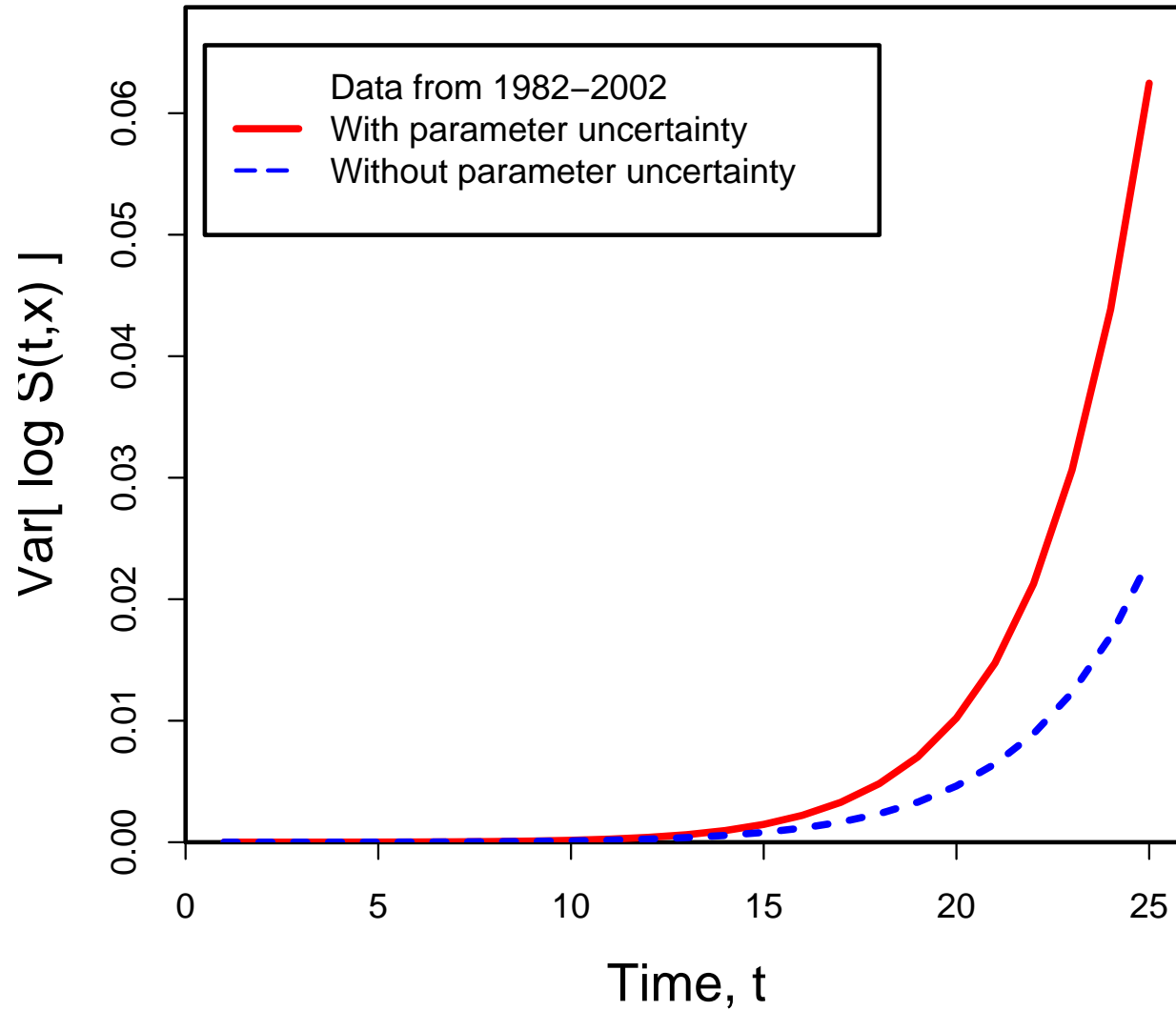
proportion surviving from time 0 to time t

$$S(t, x) = (1 - q(0, x)) \times (1 - q(1, x + 1)) \times \dots \\ \dots \times (1 - q(t - 1, x + t - 1))$$

90% Confidence Interval (CI) for Cohort Survivorship



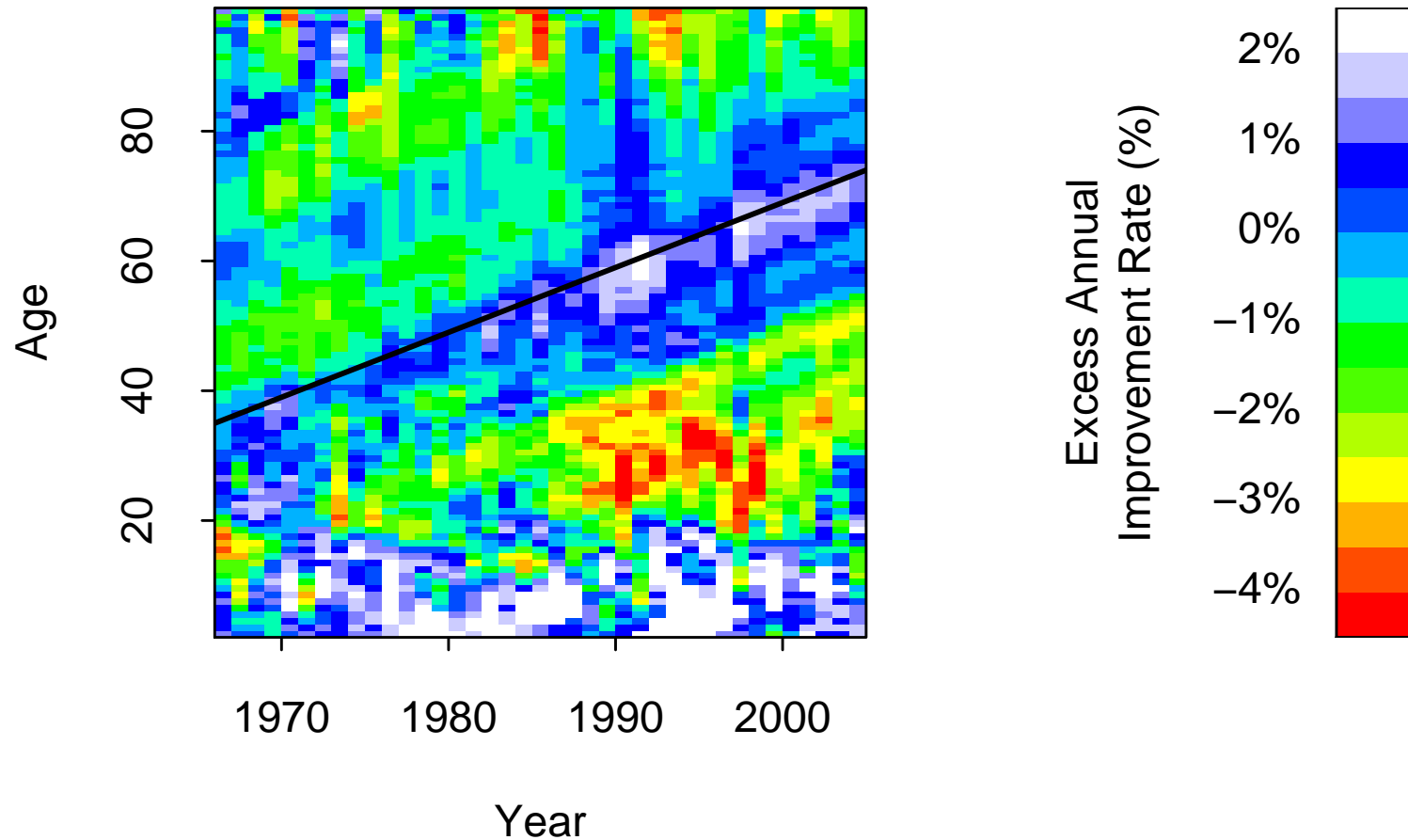
$Var[\log S(t, x)]$ for $x = 65$



Cohort Survivorship: General Conclusions

- Less than 10 years:
 - Systematic risk not significant
- Over 10 years
 - Systematic risk becomes more and more significant over time
- Over 20 years
 - Model and parameter risk begin to dominate

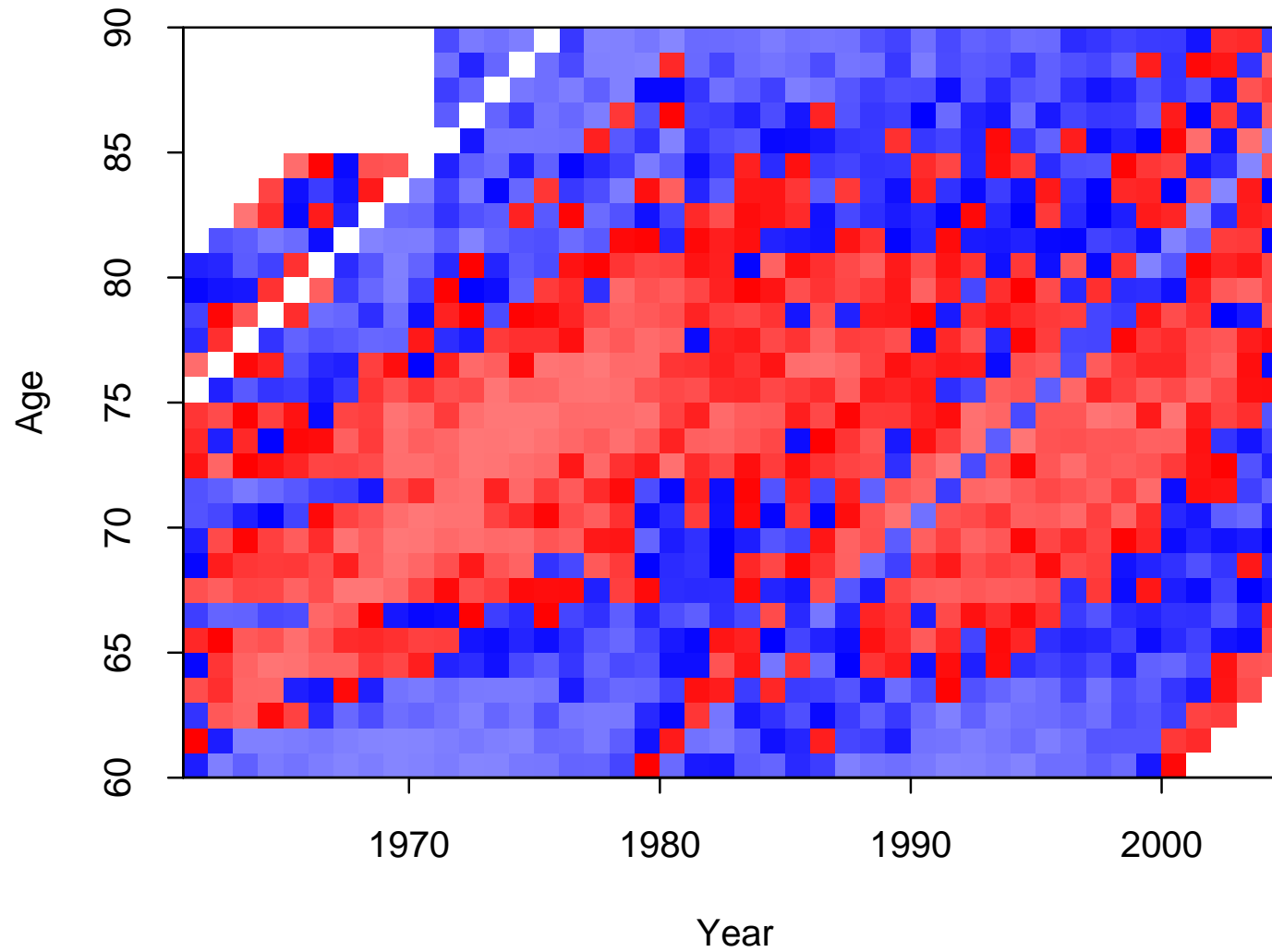
The cohort effect: England and Wales



Mortality improvement relative to calendar year average.

The Cohort Effect

2-factor Model: Standardised Residuals



TWO PARAMETRIC TIME-SERIES MODELS

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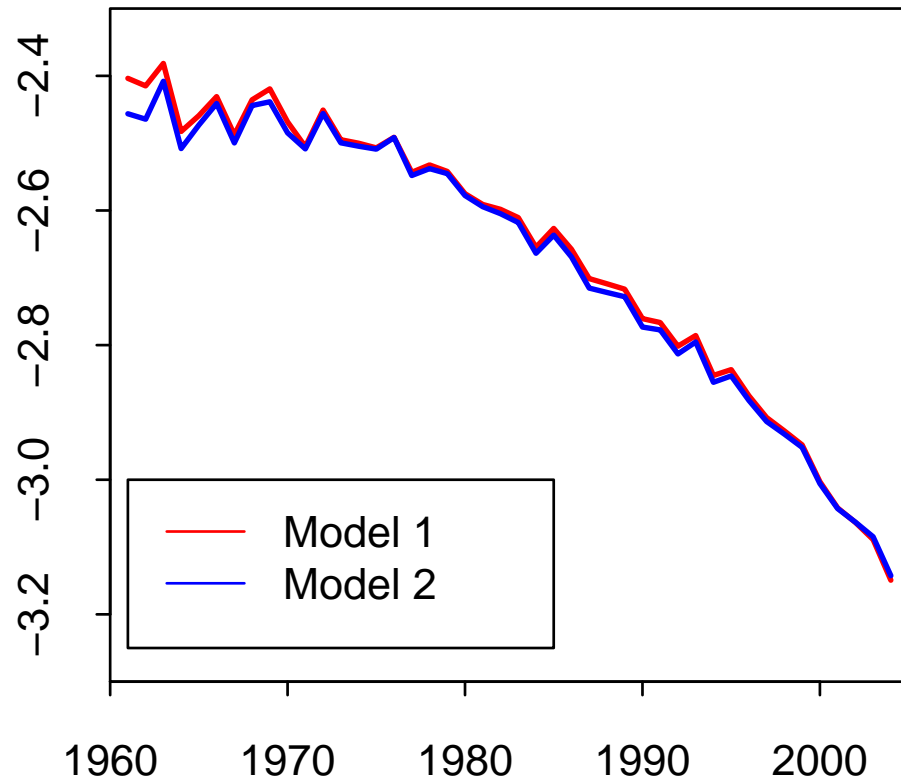
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Model 2 (Age-Period-Cohort model):

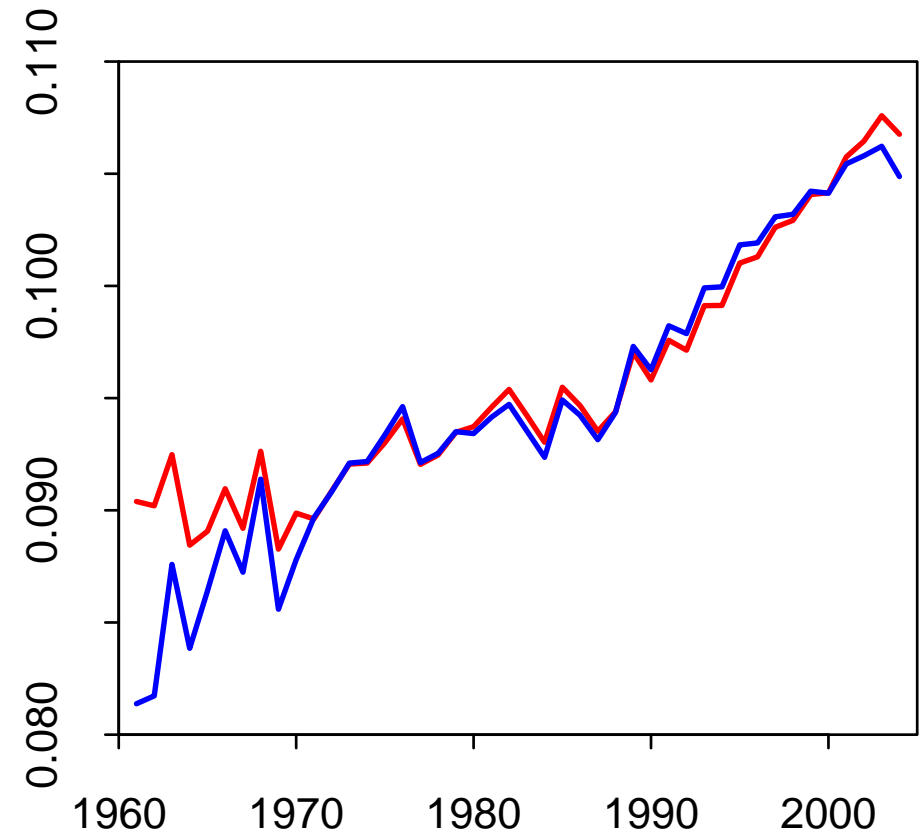
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Model 1 versus Model 2

kappa_1(t)

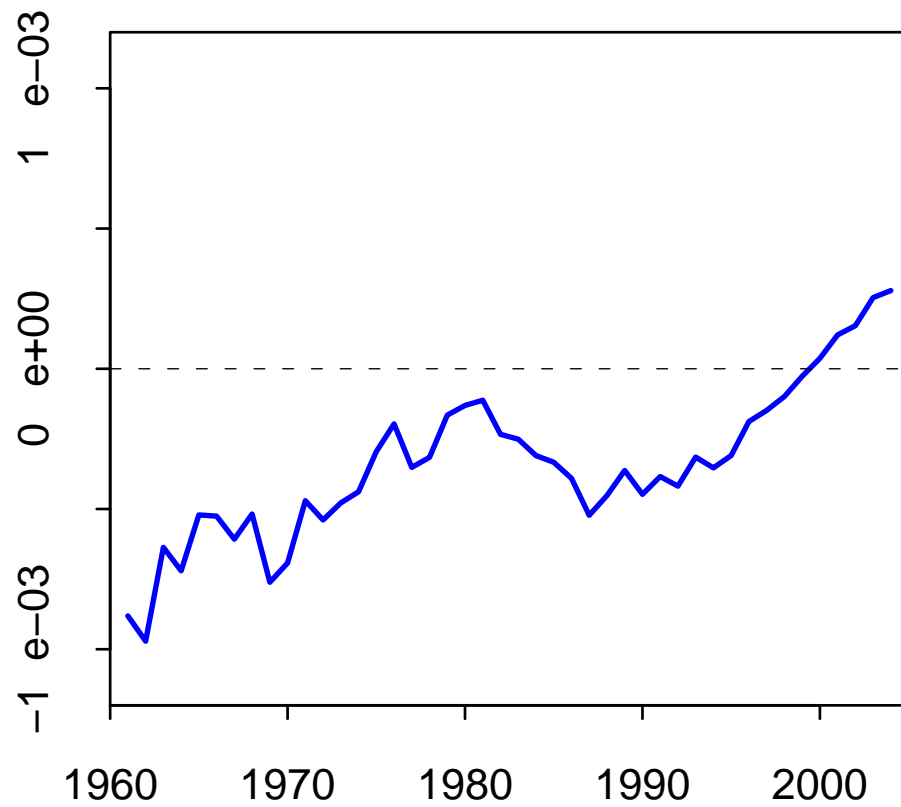


kappa_2(t)

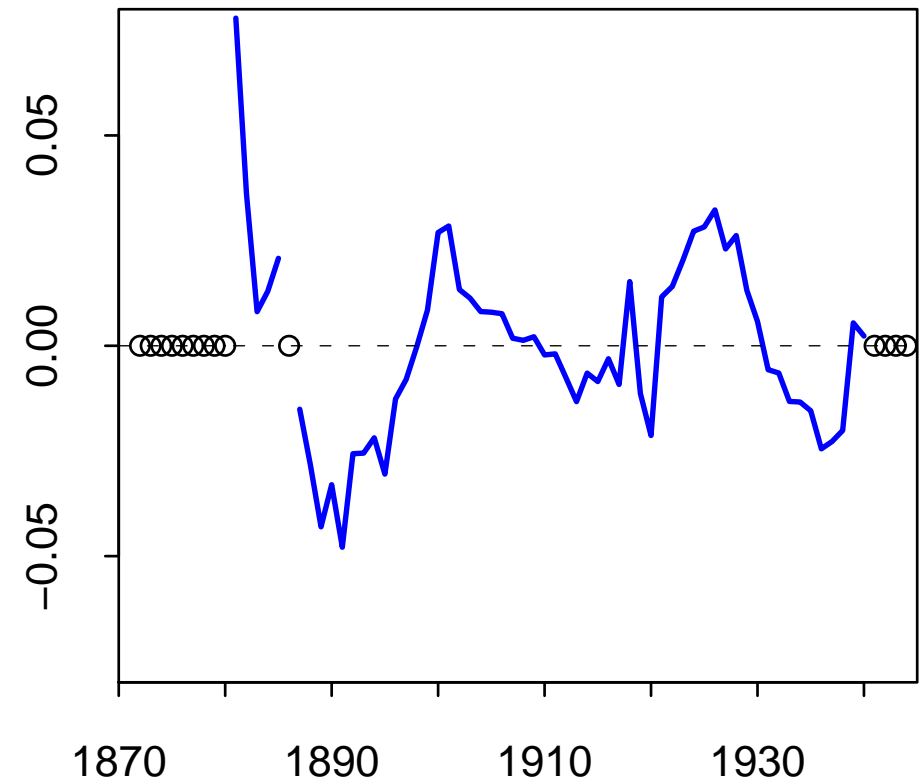


Model 2: extra factors

$\kappa_3(t)$

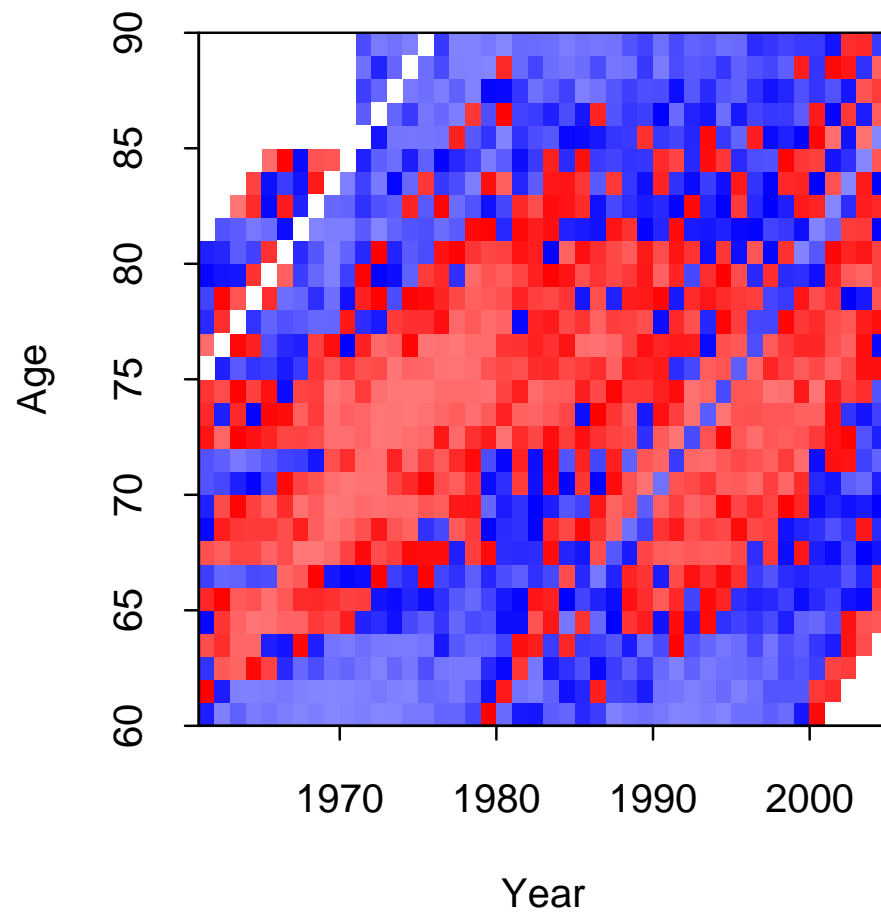


$\gamma_4(t)$

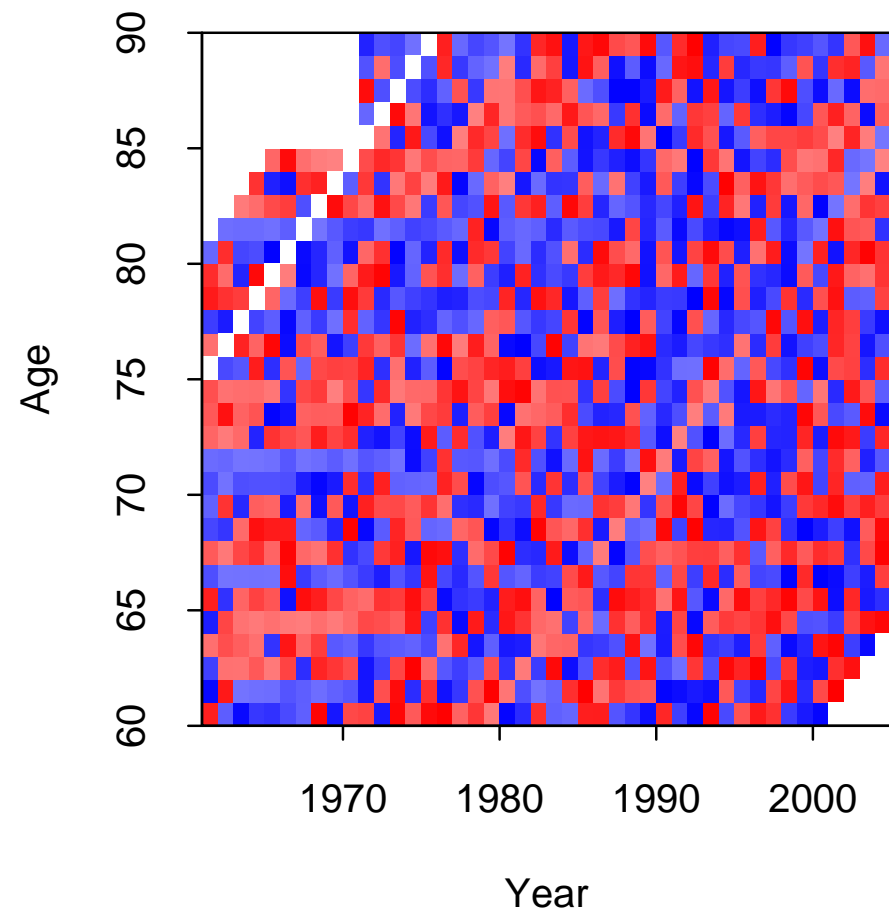


Standardised residuals

Model 1

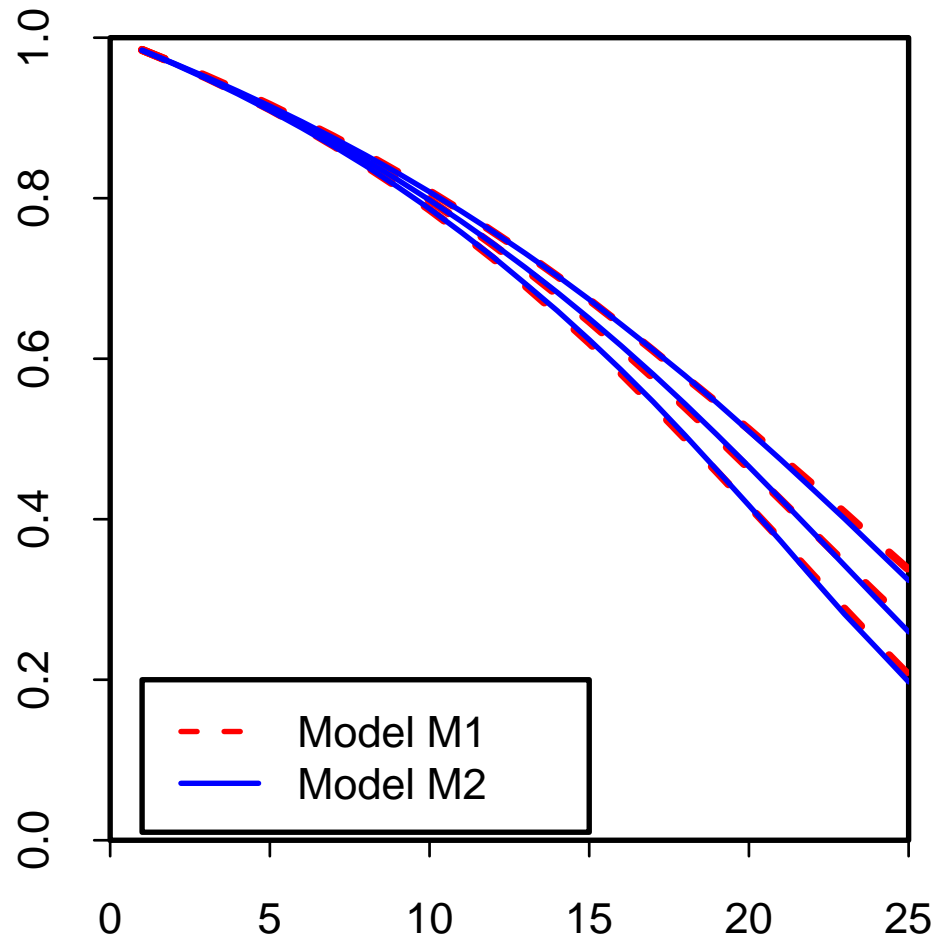


Model 2

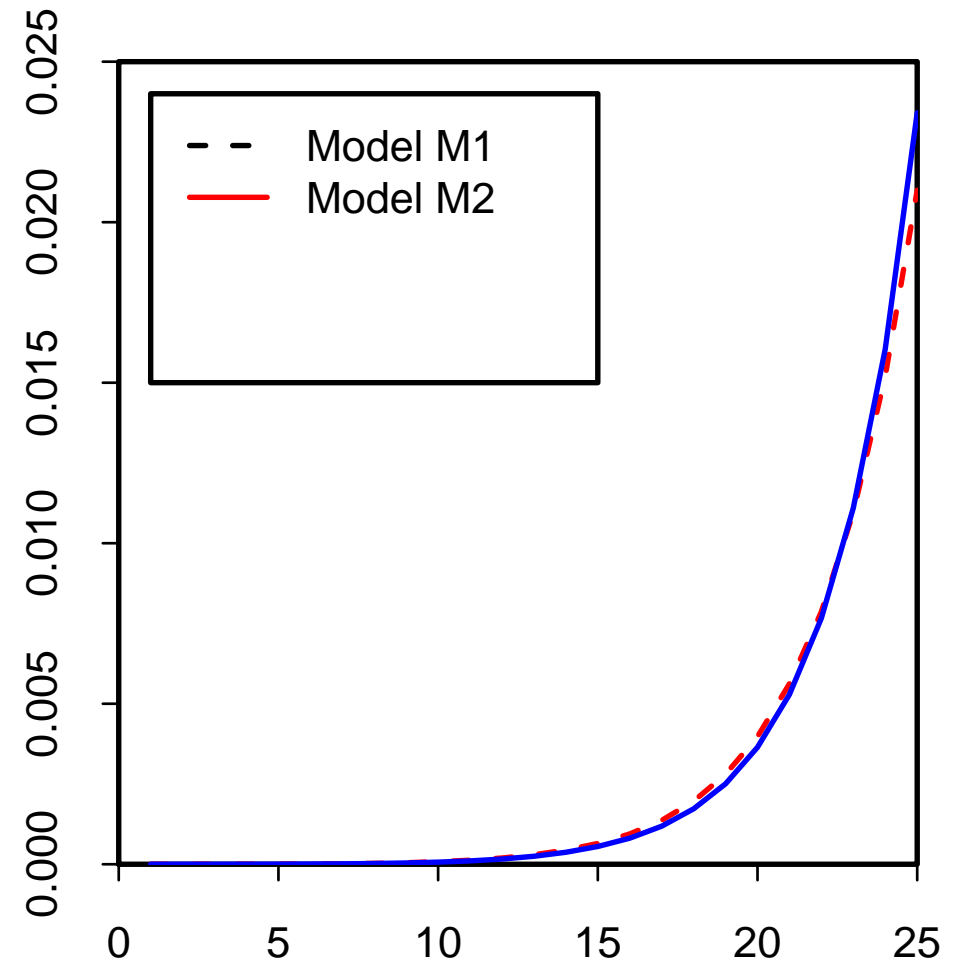


Survivor index projections

$S(t,x)$: Mean + 5%, 95% quantiles



Variance of $\log S(t,x)$



4% Annuity Values

	Model 1	Model 2	
		$\gamma_{1944}^{(4)}$ = -0.0398	$\gamma_{1944}^{(4)}$ = 0.0402
$x = 60$	13.472	13.557	13.350
$x = 65$	11.449	11.451	
$x = 70$	9.325	9.354	
$x = 75$	7.220	7.240	

Conclusions 1

- Stochastic models important for
 - risk measurement and management
 - valuing life policies with option characteristics
- Two models out of many possibilities
- **Significant** longevity risk in the medium/long term

Conclusions 2

- Parameter risk is important
- Model risk might be important
- The significance of longevity risk varies from one problem to the next:
 - In absolute terms
 - As a percentage of the total risk

Selected References

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