

# Modeling Mortality of Multiple Populations with Vector Error Correction Models: Applications to Solvency II

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# Introduction

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# Multi-Population Mortality Models

- Capture the dependence of mortality dynamics between different populations
- Useful for modeling mortality dynamics of:
  - Males and females
  - Different national populations
  - A population and its subpopulation
- Useful for estimating basis risk involved standardized longevity risk hedges

# Objectives

- A new approach for modeling mortality of multiple populations
  - Better capture the underlying correlations and long-term equilibrium
  - Does not require the user to assume which population is dominant
- An application to Solvency II capital requirements

# Three Approaches for Modeling the Time-Varying Factors

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# The Framework of Cairns et al. (2011)

- A Lee-Carter parametric structure:

$$\ln(m_{x,t}^{(i)}) = \alpha_x^{(i)} + \beta_x^{(i)} \kappa_t^{(i)}, \quad i = 1, 2$$

- Necessary conditions for non-divergence:

1.  $\beta_x^{(1)} = \beta_x^{(2)}$

2.  $\kappa_t^{(1)} - \kappa_t^{(2)}$  is mean-reverting

- The resulting forecast depends heavily on how the time-varying factors  $\kappa_t^{(1)}$  and  $\kappa_t^{(2)}$  are modeled.

# The RWAR Approach

- Used in Cairns et al. (2011)

- A random walk (**RW**) with drift for  $\kappa_t^{(1)}$ :

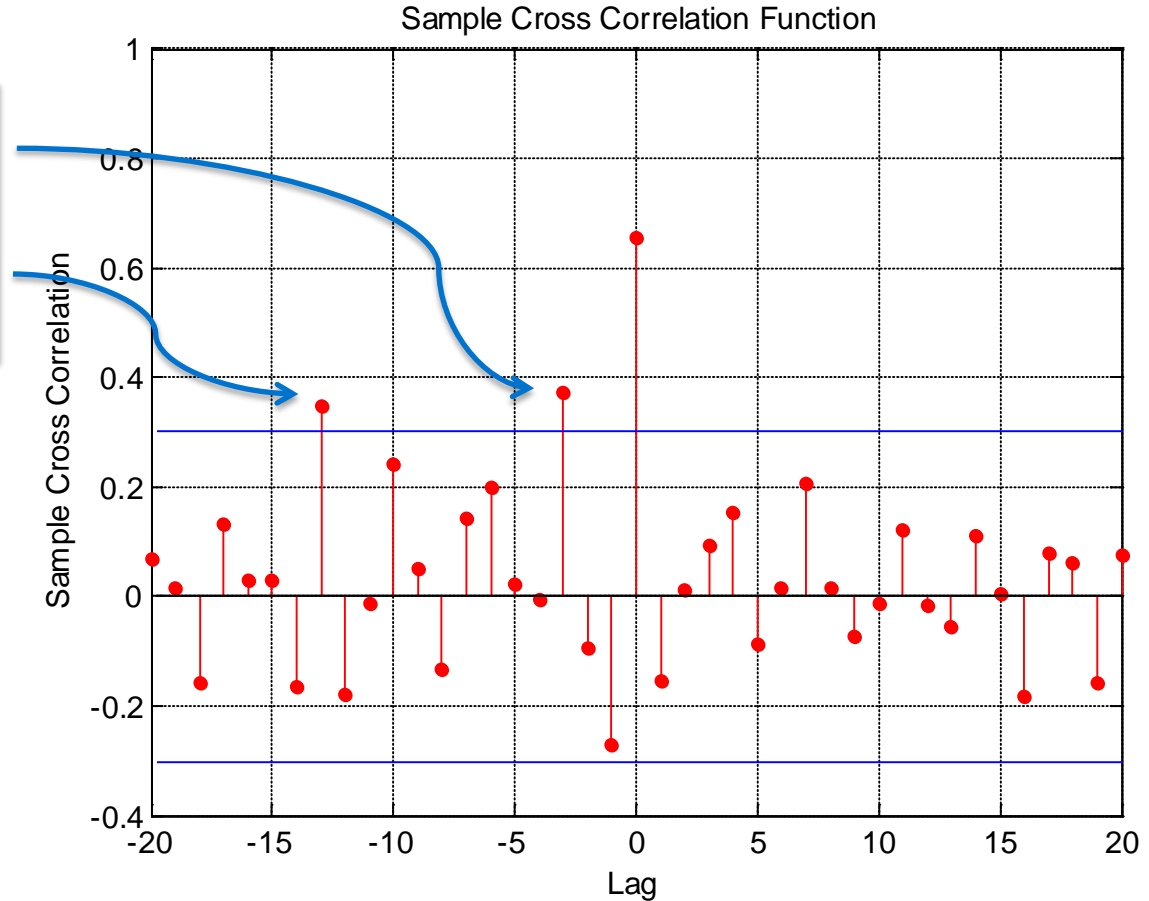
$$\kappa_t^{(1)} = \kappa_{t-1}^{(1)} + \mu + \epsilon_t^{(1)}$$

- An autoregressive (**AR**) process for  $\kappa_t^{(1)} - \kappa_t^{(2)}$ :

$$\kappa_t^{(1)} - \kappa_t^{(2)} = \mu_\Delta + \phi(\kappa_{t-1}^{(1)} - \kappa_{t-1}^{(2)}) + \epsilon_t^{(2)}$$

# The Lead-Lag Problem

Indicates that it is the CMI population that leads the EW population



Sample cross-correlations between  $\Delta\kappa_t^{(1)}$  and  $\Delta\kappa_t^{(2)}$

Population 1: EW males

Population 2: CMI males



# The VAR Approach

- A Vector Autoregressive (**VAR**) model:

$$\begin{aligned}\Delta\kappa_t^{(1)} &= \phi_0 + \phi_1\Delta\kappa_{t-1}^{(1)} + \phi_2\Delta\kappa_{t-1}^{(2)} + \epsilon_t^{(1)} \\ \Delta\kappa_t^{(2)} &= \theta_0 + \theta_1\Delta\kappa_{t-1}^{(1)} + \theta_2\Delta\kappa_{t-1}^{(2)} + \epsilon_t^{(2)}\end{aligned}$$

- Non-divergence constraint:

- $\frac{\phi_0}{1-\phi_1-\phi_2} = \frac{\theta_0}{1-\theta_1-\theta_2}$

- Ensures that  $\Delta\kappa_t^{(1)}$  and  $\Delta\kappa_t^{(2)}$  converge to the same value in the long run

# The VECM Approach

- A Vector Error Correction Model (**VECM**):

$$\Delta\kappa_t^{(1)} = \rho^{(1)} \left( a\kappa_{t-1}^{(1)} + b\kappa_{t-1}^{(2)} + c \right) + \phi_0 + \phi_1\Delta\kappa_{t-1}^{(1)} + \phi_2\Delta\kappa_{t-1}^{(2)} + \epsilon_t^{(1)}$$

$$\Delta\kappa_t^{(2)} = \rho^{(2)} \left( a\kappa_{t-1}^{(1)} + b\kappa_{t-1}^{(2)} + c \right) + \theta_0 + \theta_1\Delta\kappa_{t-1}^{(1)} + \theta_2\Delta\kappa_{t-1}^{(2)} + \epsilon_t^{(2)}$$

- Intuitions:

- $a\kappa_t^{(1)} + b\kappa_t^{(2)} + c = 0$  is the long-term equilibrium
  - $\rho^{(1)}$  and  $\rho^{(2)}$  are the adjustment coefficients
- Non-divergence constraint:  $a = -b$

# Evaluating the Three Approaches

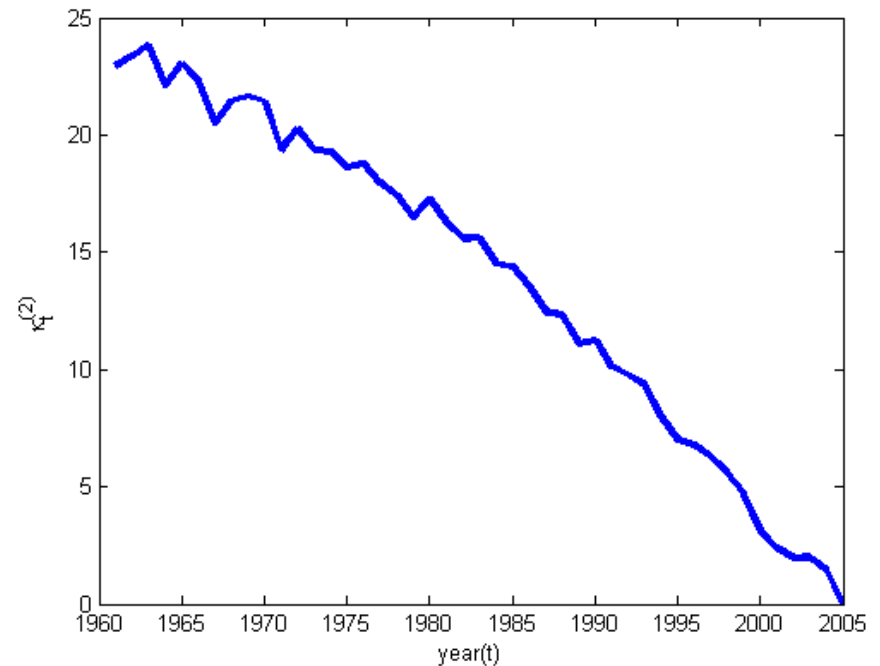
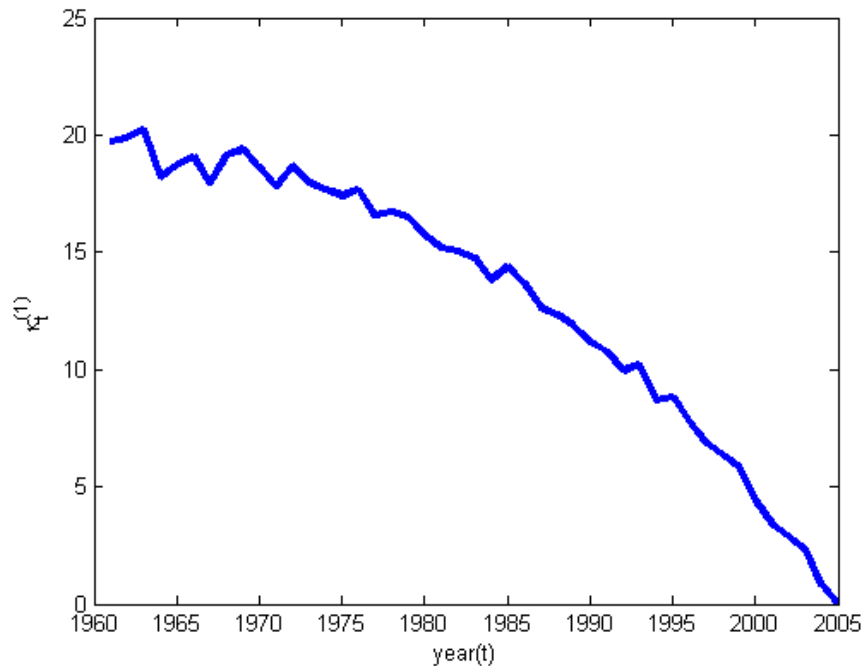
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# Evaluating the Three Approaches

- Evaluation criteria:
  - Goodness-of-fit
  - Forecasting performance
  - Robustness
- Data:
  - Population 1: EW males
  - Population 2: CMI males
  - Sample period: 1961 – 2005
  - Age range: 60 – 84

# First Stage Estimates of $\kappa_t^{(1)}$ and $\kappa_t^{(2)}$



# Goodness-of-Fit

	RWAR	VAR	VECM
BIC	179.19	176.45	174.63

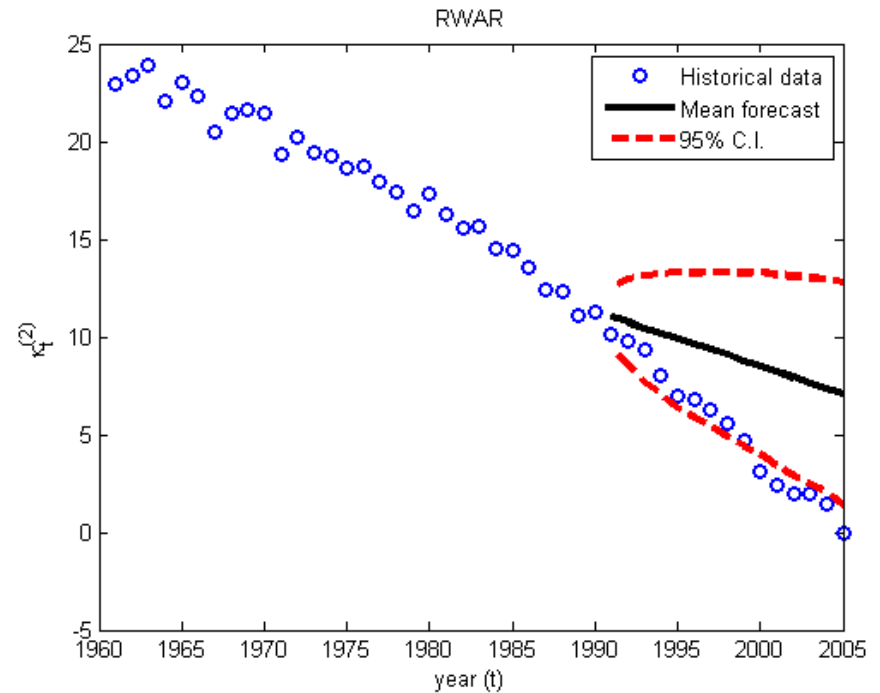
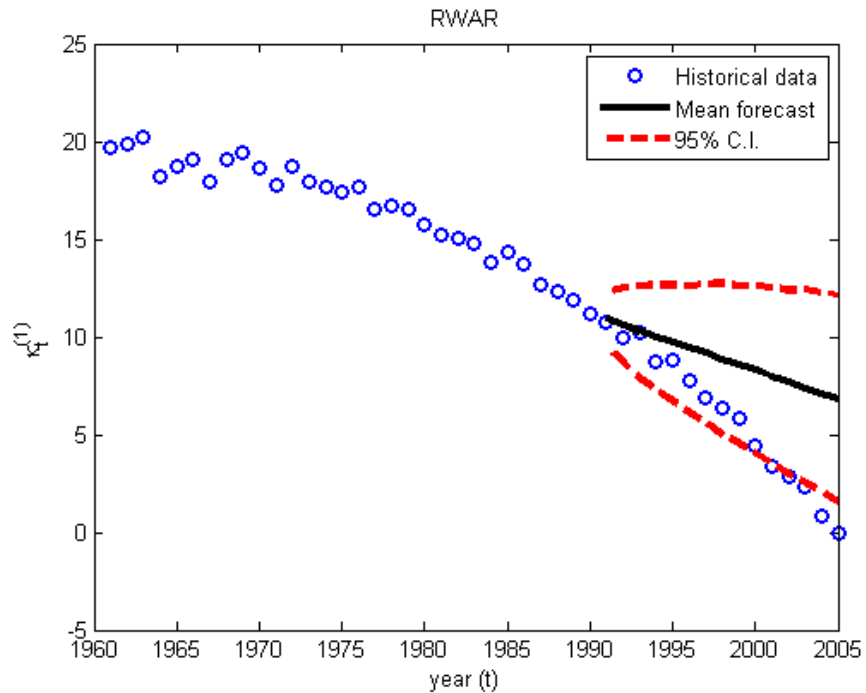
$$BIC = k \ln(n) - 2\hat{l}$$

$\hat{l}$  maximized log likelihood

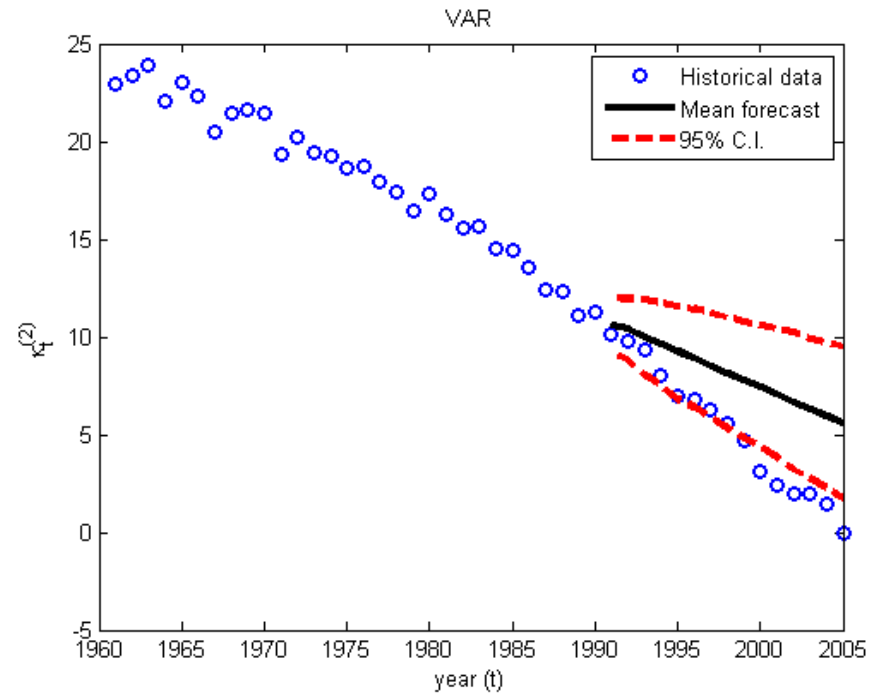
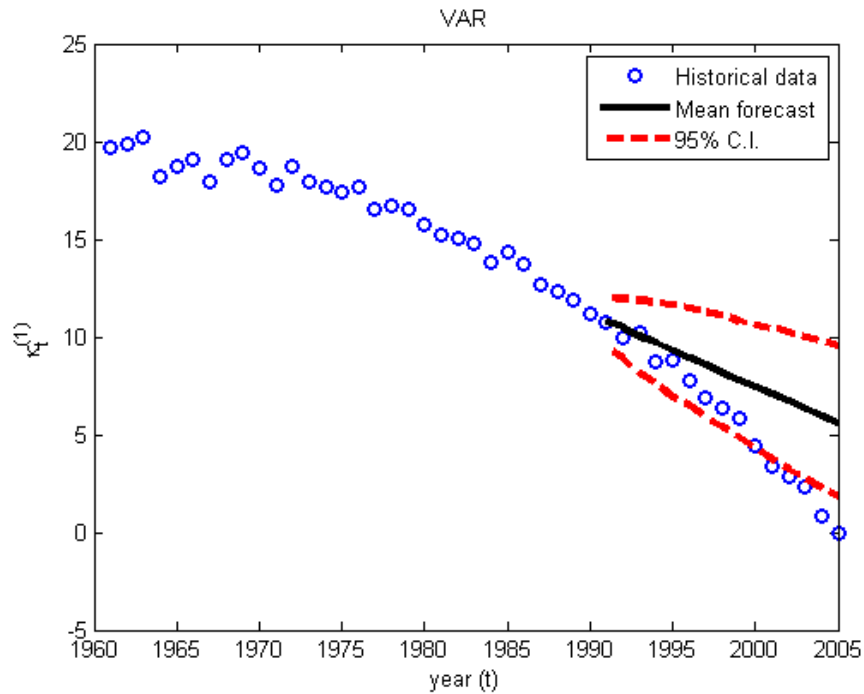
$k$  number of parameters

$n$  sample size

# In-Sample Forecast RWAR

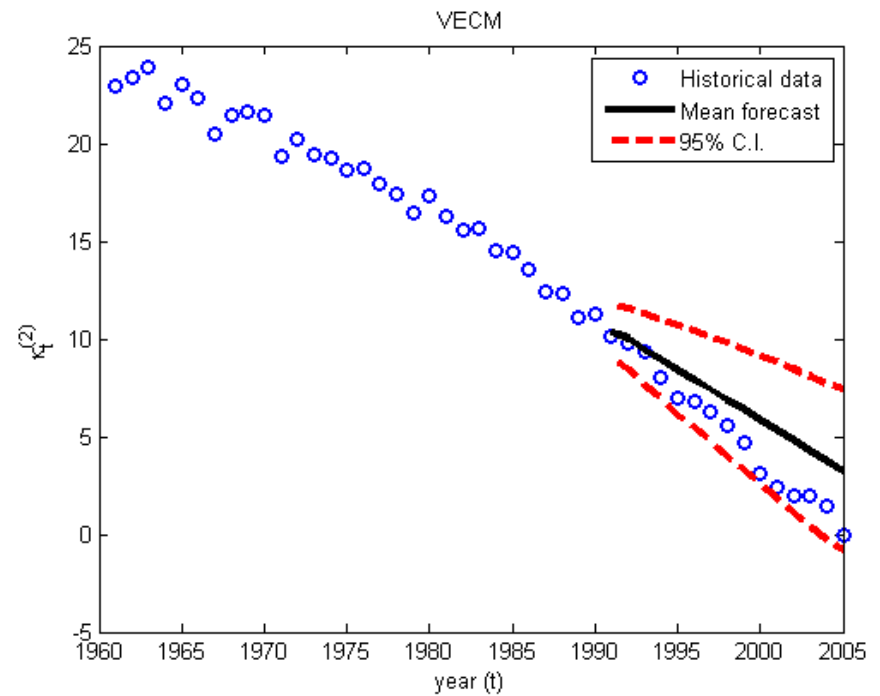
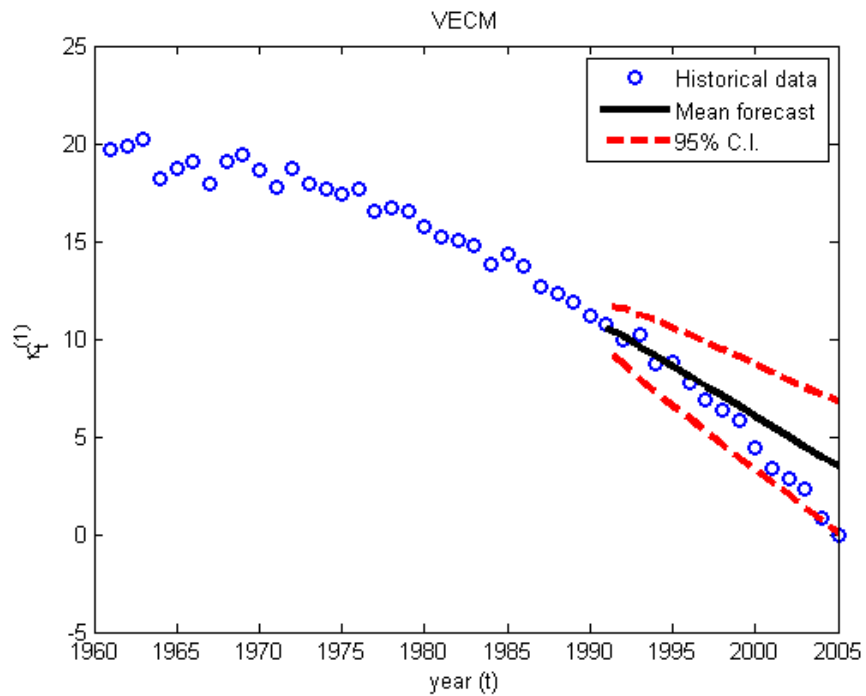


# In-Sample Forecast VAR





# In-Sample forecast VECM



# Testing Robustness

- **Test 1**

Fit the models to two different lookback periods: 1961-2005 (45 years) and 1976-2005 (30 years)

- **Test 2**

Fit the models to data over three sample periods: 1961-1990, 1966-1995, and 1971-2000

**Conclusion of Tests 1 and 2:**

VECM is the most robust among the three approaches

- **Test 3**

Examines how forecasts will change if we swap populations 1 and 2

**Conclusion of Test 3:**

VAR and VECM: No change to the resulting forecasts

RWAR: The forecasts change significantly if we swap the two populations

# Multi-Population Models Applied to Longevity Swap

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# Real-World Applications

Project survivorship of a portfolio of lives

- Pensioners, insured lives, healthy / disabled / dependent
- Current mortality: well understood
  - Experience analysis, survival models
- Future mortality trend: data?
- Use general population as a proxy
  - Introduces Longevity Basis Risk

# Longevity Basis Risk

Our case: Annuitants

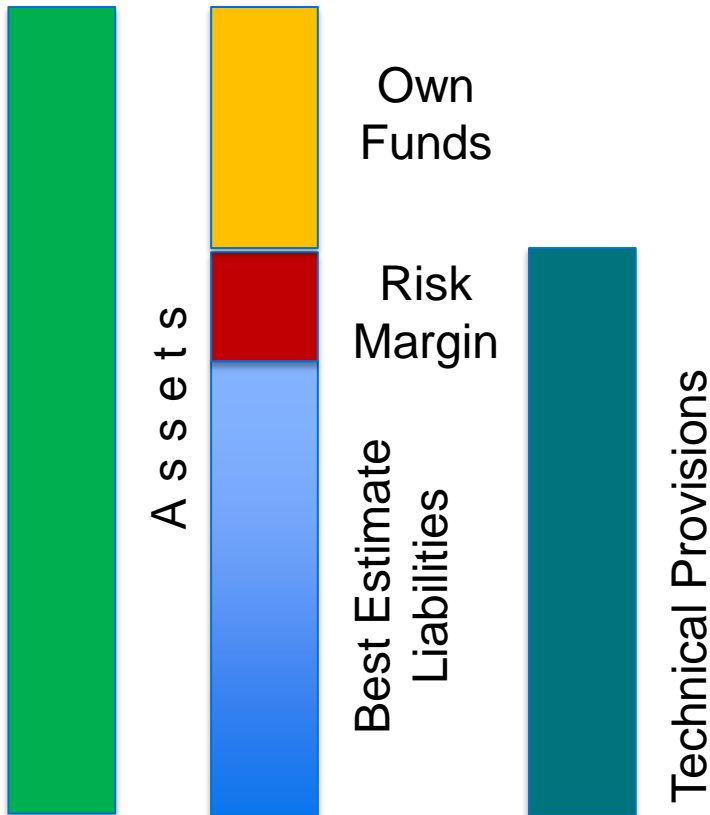
- Insured Lives vs. General Population
  - Misestimation of Best Estimate Liabilities
  - Misestimation of Capital Requirements

→ Underprice the Risk

# Longevity Swap Reinsurance

- UK: Reinsurance market  
~ £10 billion transferred per year
- Also transactions in the USA, Netherlands
- Trade **floating** pensions/annuity benefits for **fixed** stream of reinsurance premiums
- **What is the fair value?**

# Solvency 2



- Used in Cairns et al. (2011)

- A random walk (**RW**) with drift for  $\kappa_t^{(1)}$ :

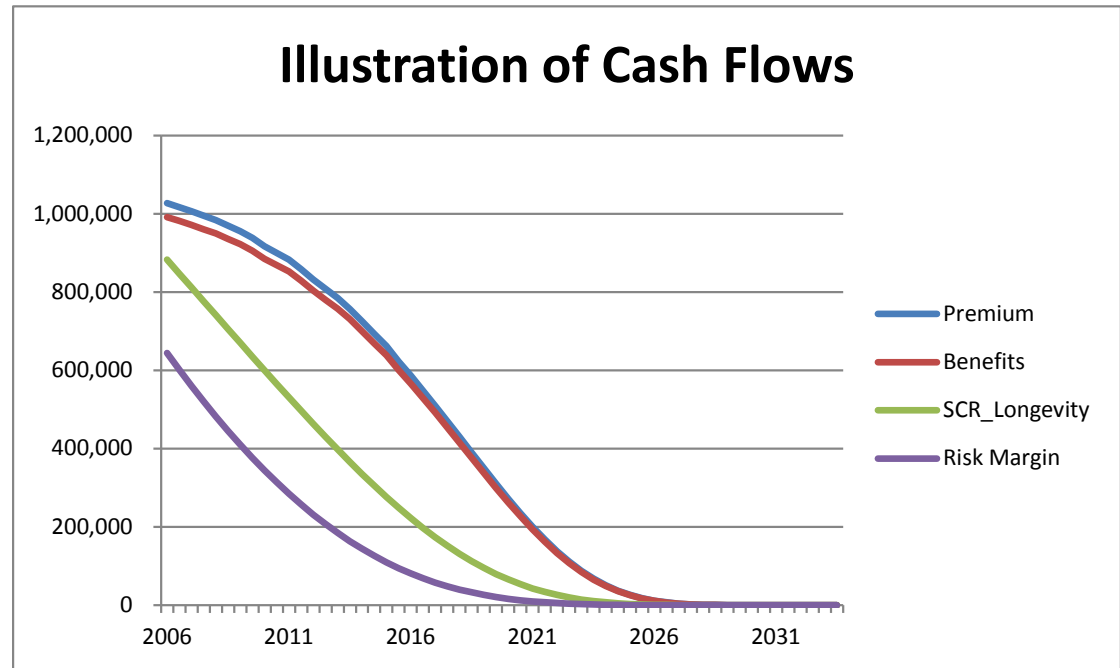
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# Longevity Swap Pricing

- Solvency Capital creates frictional cost
- Risk Margin ~ Cost of Capital



$$\text{Risk Margin} = 6\% \times PV(SCR_t)$$

$$PV(\text{Reinsurance Fees}) = \text{Risk Margin}$$



# Longevity Swap Prices

100 mn annual benefit, 99.5%-ile SCR

	<b>Single</b>	<b>RWAR</b>	<b>VAR</b>	<b>VECM</b>
Liabilities [bn]	1.679	1.697	1.701	1.728
increase		1.1%	1.3%	2.9%
Risk Margin [mn]	54.2	84.8	61.5	80.0
Risk Margin [% annual benefits]	2.0%	3.1%	2.2%	5.1%

# Longevity Swap Prices

## [Standard Formula]

100 mn annual benefit, -20% Stress SCR

	Single	RWAR	VAR	VECM
Liabilities [bn]	1.679	1.697	1.701	1.728
increase		1.1%	1.3%	2.9%
Risk Margin [mn]	86.9	86.1	89.3	91.5
Risk Margin [% annual benefits]	3.2%	3.2%	3.3%	3.3%

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